University of Alberta

Combined Fuzzy and Probabilistic Simulation for Construction Management

by

Naimeh Sadeghi

A thesis submitted to the Faculty of Graduate Studies and Research
in partial fulfillment of the requirements for the degree of

Master of Science

in

Construction Engineering and Management

Department of Civil and Environmental Engineering

Fall 2009
Edmonton, Alberta

Examining Committee

Dr. Aminah Robinson Fayek, Civil and Environmental Engineering

Dr. Yasser Mohamed, Civil and Environmental Engineering

Dr. Witold Pedrycz, Electrical and Computer Engineering

Dedication

To my family, mother, father and dear sister, that although far from me, always offered me love and encouragements.

And, to my husband, Hosein, I cannot fully express my gratitude for your unwavering support and encouragement. Without you, I could not have achieved this goal.

Abstract

Simulation has been used extensively for addressing probabilistic uncertainty in range estimating for construction projects. However, subjective and linguistically expressed information results in added non-probabilistic uncertainty in construction management. Fuzzy logic has been used successfully for representing such uncertainties in construction projects. In practice, an approach that can handle both random and fuzzy uncertainties in a risk assessment model is necessary. In this thesis, first, a Fuzzy Monte Carlo Simulation (FMCS) framework is proposed for risk analysis of construction projects. To verify the feasibility of the FMCS framework and demonstrate its main features, a cost range estimating template is developed and employed to estimate the cost of a highway overpass project. Second, a hybrid framework that considers both fuzzy and probabilistic uncertainty for discrete event simulation of construction projects is suggested. The application of the proposed framework is discussed using a real case study of a pipe spool fabrication shop.

Acknowledgement

I would like to thank Dr. Robinson Fayek and Dr. Pedrycz for their time and direction during my research as well as Dr. Yasser Mohamed for his service on this evaluation committee and Dr. AbouRizk for providing valuable feedbacks and ideas during the course of this thesis. I extend a special thank to my supervisor, Dr. Robinson Fayek, for her friendship and Mentorship.

Loving thanks to my parents for their never-ending love and support in all my efforts. Thank you, Mom and Dad. And, thank you Saideh, my dear sister, for your love and encouragements. I offer special thanks to Hosein, my loving husband and soul mate, for always being there for me. Thank you for your continual love, support, and patience as I went through this journey. I could not have made it through without you by my side.

Many thanks to my friends and fellow graduate students for all the supports and encouragements. And, to those who supported me in the mechanics of producing this thesis. Last but not least, most of all thanks to God the Divine who continues to make the impossible possible.

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CHAPTER 1 - INTRODUCTION

1.1 Uncertainty in Construction

Construction processes are affected by various uncertain variables such as weather changes, breakdown of equipment, labour deficiency, and delayed delivery of resources; these factors are unpredictable and may lead to the construction project failure (Zhang et al. 2003). However, because of the complexity of construction projects, the planner is generally incapable of considering the combined impact of uncertainties to produce reliable project estimates (Ahuja and Nandakumar 1984). Therefore, appropriate methods for representing uncertainties and predicting the effect of uncertain factors on construction processes are of great importance to effective construction planning. Uncertain variables can be represented with different methods according to their nature and the available sources of information.

The most common method for representing the uncertainty of variables is based on probability theory. Probability theory has been studied and applied to various areas of inquiry since the 17^{th} century (Liu 2002). This type of uncertainty is called *randomness*, and statistical analysis can be used for predicting its behaviour.

In practice, the probability of an event can be estimated according to the frequency of that event occurring in a number of experiments (Pedrycz 1998). In this case, it is assumed that the nature of the variable is random and that we have samples of real numbers of that variable. However, if the number of experiments is not large enough to be significant, and more experiments cannot be performed, it is not possible to accurately estimate the event's probability. Furthermore, some factors, such as worker's skill and complexity of the work, are subjective. In these circumstances, we can engage human experts who are usually adept at supplying required information of this nature. Nevertheless, the information gained from experts is subjective and contains ambiguity. AbouRizk and Halpin (1992) suggest that subjective judgment of the modeler can be used for selecting the best probabilistic distributions for these uncertain variables. However, experts usually think in linguistic terms such as *much*, *very*, *big*, etc. rather than probability values (Kim and Fishwick 1997). As a result, subjectively selecting the probability distributions may lead to inaccurate representation of the uncertainty (Shaheen 2005).

Fuzzy set theory (Zadeh 1965) provides a methodology for handling linguistic variables and representing uncertainty in the absence of complete and precise data. Fuzzy logic methods have been used successfully in various types of construction applications. For example, fuzzy logic approaches have been implemented for project scheduling (Lorterapong and Moselhi 1996), predicting industrial construction labour productivity (Fayek and Oduba 2005), and cost estimating (Shaheen et al. 2007), to indicate some representative examples.

In conclusion, when modeling uncertain variables in a construction problem, we may face two different scenarios (AbouRizk and Halpin 1992):

a) Historical data are available for the uncertain variable, and we can use probability theory.

b) The variable is subjective or sufficient historical data is not available for that variable. We can benefit from experts' information about the uncertain variable and use fuzzy set theory for representing that information.

Therefore, probabilistic approach and fuzzy set theory can play a complementary role in representing the uncertainties of constructing projects.

1.2 Problem Statement

Risk analysis is usually performed on construction projects in order to identify potential issues ahead of time and to consider contingency. For this purpose, the effect of different uncertain factors on the productivity, cost, schedule, etc. are estimated.

Simulation is a method for risk analysis of construction projects. Monte Carlo simulation is a method for estimating the effect of random variables on complex problems using computer programs (Liu 2002). Furthermore, discrete event simulation can be used to analyze the sensitivity of dynamic schedule and resource constraints to unexpected construction scenarios, while Monte Carlo simulation is applied to a model that does not depend on time. Since construction projects are usually complex in nature, simulation methods are extensively used in construction management for risk analysis of projects in which all uncertain variables are random (Ahuja and Nandakumar 1984).

In risk analysis of construction projects, one may also face a project in which all the uncertain variables are fuzzy. This situation usually happens when human judgment and decisions are the most important factors, such as forecasting seasonal runoff (Mahabir et al. 2003) or performance prediction and evaluation (Fayek and Sun 2001). Fuzzy calculus is used for analytically calculating the impact of different fuzzy variables on the output. Fuzzy rule-based systems allow the user to linguistically express the impact of different variables using if-then rules. Furthermore, fuzzy discrete event simulation provides the capability of considering fuzzy sets for the durations of the activities in discrete event simulation.

The problem arises when we face a combination of fuzzy and random uncertainty. These situations are common in construction projects, where each project is unique and only limited data are available for many factors affecting a project while other factors can be addressed through historical data. Risk analyzers of construction projects usually fail to make appropriate use of available data and expert's judgment simultaneously. Monte Carlo simulation framework is the most common risk analysis method in construction management, but this framework does not accept fuzzy types of uncertainty as for the input variables. As a result, the effect of subjective variables such as weather conditions and labour skill level cannot be modeled with fuzzy set theory, although these factors highly affect the productivity of construction projects. Some researchers try to incorporate subjective factors in simulation models by modifying the fitted distributions based on the impact of linguistic descriptors (for example, AbouRizk and Sawhney 1993, Ayyub and Haldar 1984). In these methods, the existence of a primary probabilistic distribution is assumed. Furthermore, the final variable is represented in the form of a probability distribution and cannot fully represent the imprecision in the input variables resulting from linguistic expressions. Shaheen (2005) feeds the crisp output of a fuzzy rule-based system to the input parameters of a simulation model. However, he does not build fuzzy inputs directly to the model.

Since the appropriate representation of input parameters highly affects the reliability of the output of a risk analysis project, having a framework that can handle both fuzzy and probabilistic uncertainty is very essential for construction management. This framework enables us to incorporate the expert's knowledge and historical data in risk analysis of the projects and to explicitly account for both random and fuzzy uncertainty.

1.3 Research Objective

In order to address the issues discussed in section 1.2, a Fuzzy Monte Carlo Simulation (FMCS) framework is proposed, which, for the first time, provides the capability of considering fuzzy and probability uncertainty simultaneously for risk analysis of construction projects. Furthermore, a framework for considering both fuzzy and probabilistic uncertainty in discrete event simulation is suggested. The objectives of this thesis are as follows:

1. To develop a novel approach for dealing with two types of fuzzy and probabilistic inputs based on the mathematical foundations of fuzzy and probability theory.

2. To represent the output of FMCS containing randomness and fuzziness by using fuzzy random variables and calculating the mean and variance of the output.
3. To propose fuzzy Cumulative Distribution Function (CDF) as a novel approach for risk analysis that is capable of considering both types of, fuzzy and random, uncertainties in a single diagram.
4. To experiment with the consistency of FMCS framework and Monte Carlo simulation in the absence of fuzziness. Since the FMCS framework is a generalized form of Monte Carlo simulation, its results should be equal to Monte Carlo simulation in its extreme case, where we have purely probabilistic inputs.
5. To develop a cost range estimating simulation template based on the FMCS method. This template will illustrate one of the practical aspects of FMCS in construction management by providing the capability of considering both fuzzy and probabilistic uncertainty for input variables.
6. To illustrate the feasibility of the proposed FMCS framework and fuzzy CDF method using an example of cost range estimation for a highway overpass project.
7. To discuss the need for a generalized form of discrete event simulation that is capable of considering both fuzzy and probabilistic uncertainty for modeling industrial construction projects.
8. To propose a combined fuzzy and probabilistic framework for discrete event simulation using industrial fabrication as an example.

In conclusion, this thesis attempts to propose a generalized form of Monte Carlo simulation called Fuzzy Monte Carlo Simulation (FMCS) to enhance risk analysis methods in construction management. It also discusses a discrete event simulation framework that is capable of considering both fuzzy and probabilistic uncertainty for modeling construction projects.

1.4 Thesis Organization

The remainder of this thesis is organized as follows:

Chapter 2, first provides a background to Monte Carlo simulation, discrete event simulation, fuzzy risk analysis, and fuzzy discrete event simulation. Second, it reviews available literature in which fuzziness and probabilistic information are considered simultaneously.

Chapter 3 outlines the Fuzzy Monte Carlo Simulation Framework (FMCS). Fuzzy Cumulative Distribution Function (CDF) is introduced as a generalized form of CDF for modeling the output of FMCS framework in this chapter. Finally, the development of a FMCS range estimating template and its practical applications through an example of a construction project is illustrated.

Chapter 4 proposes a new approach for discrete event simulation of industrial construction projects through a case study of pipe spool fabrication. Methods for enhancing the developed simulation model are discussed, and a framework for considering combined fuzzy and probabilistic uncertainty for discrete event simulation framework of industrial construction projects is proposed.

Chapter 5 discusses the conclusions and contributions of this thesis. In addition, limitations and future developments are explained in this chapter.

CHAPTER 2 - Background

2.1 Introduction

This chapter reviews the extant literature to provide a background and to review the previous methods to justify the need for developing combined fuzzy and probabilistic simulation for risk assessment of construction projects. A brief background in these areas is provided in Section 2.2 and 2.3 respectively. In Section 2.2, simulation is introduced as a tool for risk analysis of construction projects when facing random type of uncertainty. Risk analysis using fuzzy logic is discussed in section 2.3.

Section 2.4 provides a state of art review regarding the main concern of this research, which is risk analysis when facing both fuzzy and random input parameters in a model. Finally, Section 2.5 summarizes the discussions and concludes the requirement of further steps to be developed based on the current state of research in risk analysis of construction projects.

2.2 Simulation in Construction

Simulation is a very powerful tool for modeling real life situations. Due to the unreliable environment and complex process of construction projects, simulation has been proposed as an indispensable problem-solving methodology for analyzing construction processes (Halpin and Riggs 1992). Monte Carlo simulation is applied to a model that does not depend on time, while time dependant or dynamic simulation is divided into two general categories: Continuous simulation and discrete event simulation. In continues simulation, differential equations are used to model the progress of an activity. Discreet event simulation is utilized when mathematical modeling is not possible (Hajjar 1999). In the following Sections, a brief background on Monte Carlo simulation and discrete event simulation is provided.

2.2.1 Monte Carlo Simulation for Construction

Monte Carlo simulation has been used extensively for addressing probabilistic uncertainty in construction projects, for example for estimating the duration or cost of a construction project (Ahuja et al. 1994) or for schedule risks (McCabe 2003). Computer models can be used to predict the output of a system by abstracting its behavior. When probabilistic information of uncertain parameters of a computer model is provided, Monte Carlo simulation can be used to provide statistical estimations for the outputs. Probabilistic information is collected trough previous experiments of a project for variables that have random type of uncertainty and are called random variables (Ross et al. 2001).

Monte Carlo simulation performs various experiments on a model using inputs coming by sampling from the input probability distributions. Probability distributions define the probability of values of a discrete random variable. However, in an interval of continuous random variables, there are infinite number of values and the probability of getting any point is zero. Therefore a Probability Density Function (PDF) is defined on these variables. PDF can be used for calculating the probability that the random variable falls into a particular interval (Equation 2.1).

Figure 2.1 illustrates an example of a PDF and represents the probability based on the area under the curve.

$$\Pr(a < x < b) = \int_b^a f(x)dx \tag{2.1}$$

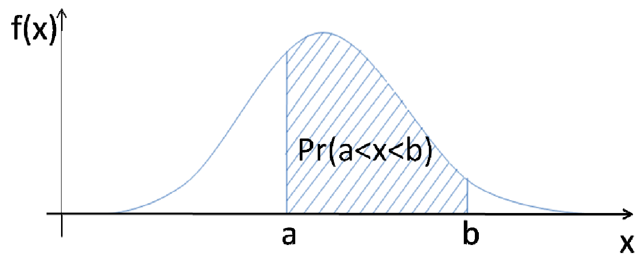


Figure 2.1 Probability Distribution Function (PDF) f(x) of random variable x and the probability that this variable falls into interval (a,b)

The Monte Carlo simulation method is used for estimating the output (Y) of a model (g) with random input variables ($\mathrm{R}_1, \mathrm{R}_2, \dots, \mathrm{R}_\mathrm{n}$) (Figure 2.2.a). The process of a Monte Carlo simulation is explained in the following steps (Ahuja et al. 1994). This procedure is also illustrated in Figure 2.2.b.

1. Sample n values $r_1, r_2, \dots, r_n$from the probability distributions of the random inputs $R_1, R_2, \dots, R_n$
2. Assign the values to the model and calculate the output: *Y*=*M*($r_1, r_2, \dots, r_n$)
3. Store the output *Y*
4. Repeat steps 1 to 3 for i=1 to k
5. Perform statistical analysis on the collected outputs

The number of iterations, k, depends on the level of accuracy that is required in a model. Having too few iterations results in inaccurate output, while too many iterations requires too much time to run the model. The accuracy of the model with k iterations can be estimated as the variance of required statistics (VOSE software).

For decision making purposes, the mean and variance of the output of Monte Carlo simulation are the most important statistics that are typically calculated. If we run a simulation model for k independent times and record the output Y_i $(i = 1, \ldots, k)$, the sample mean $(\overline{Y})$ and variance (s^2) can be calculated indicated in equations 2.2 and 2.3 respectively.

$$\overline{X} = \frac{\sum_{i=1}^{k} Y_i}{k} \tag{2.2}$$

$$s^2 = \frac{1}{k} \sum_{i=1}^{k} (Y_i - \overline{Y})^2 \tag{2.3}$$

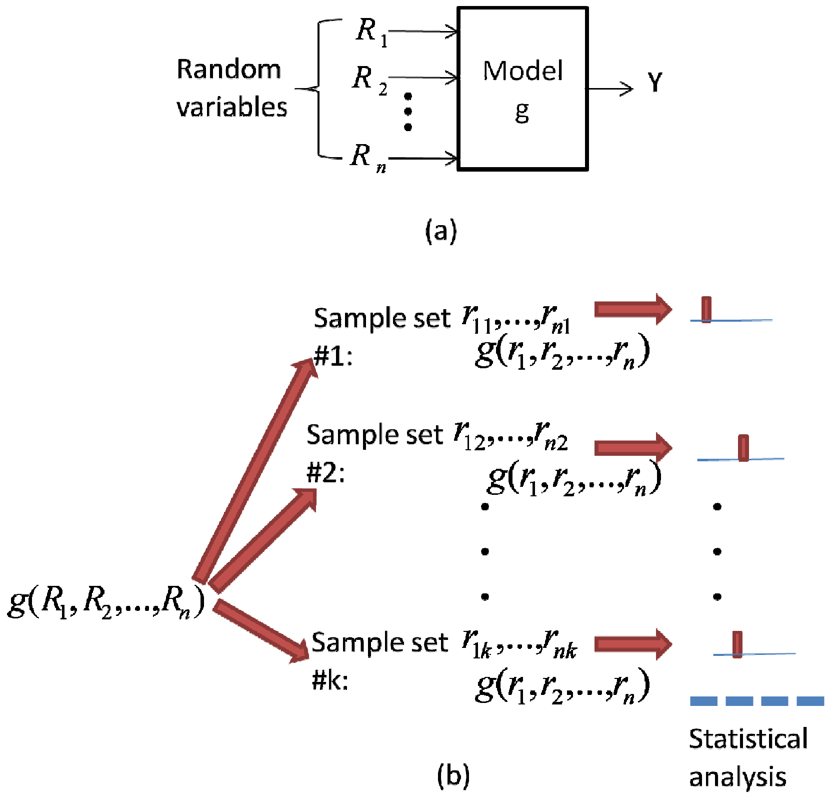


Figure 2.2 (a) A model g with random inputs can be calculated with Monte Carlo simulation (b) Process of Monte Carlo simulation

Furthermore, in construction management, a decision-maker is usually interested in two other important statistics: (1) an arbitrary quantile, and (2) the probability of exceeding (or not exceeding) a specific threshold. For example, one may want to estimate the completion time of a project with 95% confidence. This value is referred as the 95th quantile of the output. In the context of the simulation process, this means that 95% of the conducted simulation results are less than the completion time. Decision-makers are also interested in finding the probability that a project will exceed a certain value of cost or time (Ahuja et al. 1994).

The Cumulative Distribution Function (CDF) is typically used for finding the probability of not exceeding a given threshold. Equation 2.4 defines the CDF function of a random variable X (Ahuja et al. 1994). The CDF can be calculated based on PDF f(x) using Equation 2.5.

$$\mathrm{F_X(x)} = \Pr\{\mathrm{X} < x\} \tag{2.3}$$

$$\mathrm{F(x)} = \int_{-\infty}^{x} f(t)dt \tag{2.4}$$

Considering a finite number of random samples resulted from k experiments, CDF function can be estimated with Equation 2.6.

$$F_X(t) = \frac{Number\ of\ samples\ that\ are\ less\ than\ t}{k} \tag{2.6}$$

The inverse of the CDF is used for finding the arbitrary quantile. Figure 2.3.b indicates the use of CDF F(x) for finding the 90th quantile of a random variable.

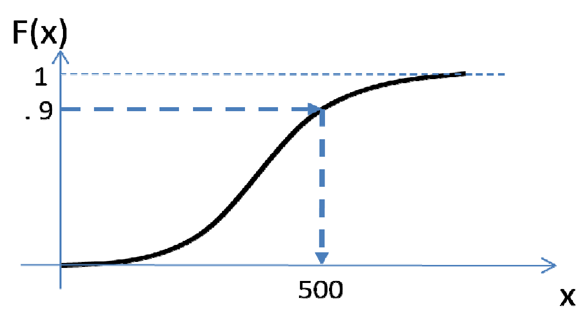


Figure 2.3 Using the inverse CDF to find the 90th quantile of random variable x

2.2.2 Discrete Event Simulation in Construction

Discrete event simulation is defined as a chronological sequence of events and transitions between those events. In discrete event simulation, the events are managed in an event list. The system determines the time advance step based on the next event that will occur. Accordingly, the forthcoming event is removed from the event list, and the state of the system is updated. As soon as the time is advanced, new events may be added to the event list. Simulation time or TNOW represents the time that in which the current event takes place. A simulation clock keeps track of the simulation time (Halpin and Riggs 1992).

Many discrete event simulation frameworks have been developed to ease the use of discrete event simulation in construction projects, including CYCLONE (Halpin 1976), COOPS (Liu and Ioannou 1992), CIPROS (Tommelein and Odeh 1994), and STROBOSCOPE (Martinez and Ioannou 1994). These frameworks use real values or probabilistic distributions to represent the durations of events in the simulation model. When probabilistic inputs are used, sample values of probabilistic distributions are used for the duration of each event in discrete event simulation. In these circumstances, the model is run through various times, and statistical analysis is performed on the outputs resulting from different runs.

2.3 Fuzzy Logic Methods in Construction

Fuzzy logic methods have been used for considering subjective variables and expert's judgment for construction management. Fuzzy sets and fuzzy logic techniques deal with linguistic terms that are used widely in construction related problems. Fuzzy logic provides a methodology for handling linguistic variables and facilitates common sense reasoning for modeling complex systems, such as management systems, especially in the absence of complete and precise data. It can be applied for forecasting, decision-making, or control of actions in any environment that

that deals with uncertainty, vagueness, impression, and subjectivity (Bojadziev and Bojadziev 1997; Zhang et al. 2003; Gilberto 2007). Fuzzy methods were used successfully in various types of construction projects. For example, it is implemented for project scheduling (Ayyb and Haldar 1984; Zayed and Halpin 2004), and for predicting industrial construction labour productivity (Fayek and Oduba 2005). Fuzzy set theory has been integrated with continuous simulation to modeling uncertain production environments (Dohnal 1983; Fishwick 1991; Negi and Lee 1992; Southall and Wyatt 1988).

A fuzzy set is defined on a set of objects by assigning a membership degree between 0 and 1 to each object. The membership degree indicates the degree that the objects are compatible with the properties of the fuzzy set (Pedrycz 1998). Therefore a fuzzy set mimics the human way of thinking by providing shades of gray rather than working with black and white (Shaheen 2005). For example, assume that we want to assign the concept of tall or short based on the height of a person. in traditional sets, a magic threshold should be considered for separating short and tall people. In addition, a person is considered whether short or tall just because of 1 (cm) height difference (Figure 2.4 (a)). Fuzzy set theory allows us to express this concept by assigning a degree of being short or being tall based on the height of different people. Figure 2.4(b) illustrates how shadows of gray are defined for the height to represent degrees of being short or tall (Pedrycz and Gomide 2007). This way of representation is closer to the human way of thinking, since we usually consider a degree for these concepts, for example we may say a person is almost tall or not very short.

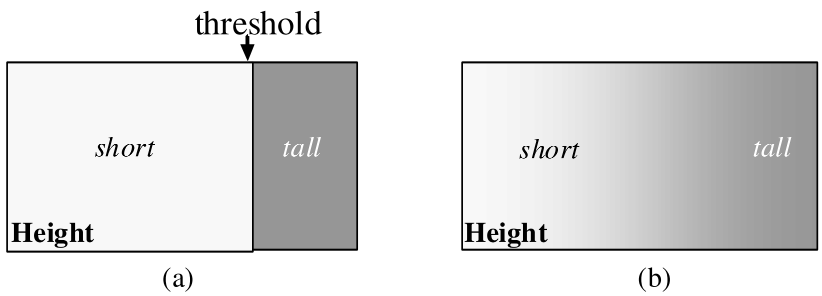


Figure 2.4 Representing the concepts of short and tall based on the height of the people.

a) Using traditional sets b) using fuzzy sets (Pedrycz and Gomide 2007)

A fuzzy set A on the universal set X is defined by its membership function $\mu(x)$ and represents the degree that x belongs to the fuzzy set. $\mu(x)$ is mapping form X to the real unit interval [0, 1].For example, Figure 2.5 indicates the membership function of being tall; a person with height equal to 170 cm is considered to be tall with the degree of 0.7 according to this membership function. Various methods exist in the literature for developing fuzzy sets using expert's judgment. For example, horizontal method of membership estimation which is based on estimating the membership values of some selected items in the universe of discourse. In vertical method of membership estimation, the expert estimates different confidence intervals to construct the fuzzy set (Pedrycz and Gomide, 2007).

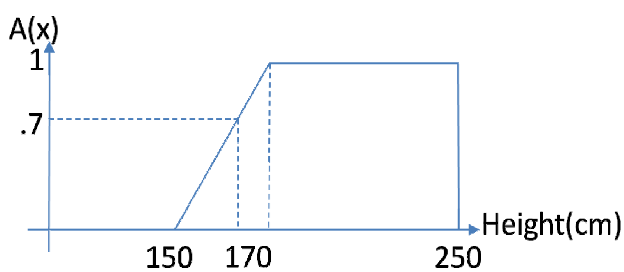


Figure 2.5 Membership function for being tall

Membership functions can have different shapes according to the available information and nature of the parameter. One of the most common membership functions is triangular; the expert can provide minimum, maximum and most possible values and a triangular PDF can be estimated based on these values. Furthermore, triangular membership functions are very appropriate for performing fuzzy arithmetic; the results of addition or subtraction of two triangular fuzzy sets is also a triangular fuzzy set. Furthermore, the results of multiplication and division of two triangular fuzzy sets can be estimated as a triangular membership function with a small error. If the expert does not have enough information about a parameter to estimate the most possible value, $\mu(x)$ can be represented as a uniform membership function, using minimum and maximum values.

Fuzzy set theory is used for construction management in two different ways: (1) fuzzy expert system (2) fuzzy calculus. Fuzzy expert systems can express expert way of thinking trough linguistically expressed rules. The inputs and output of a fuzzy expert system are crisp values. The input values go through a fuzzification interface to assign levels of truth of linguistic terms to each of the inputs. The rules are fired based on the level of truth of their premise part and the results of different rules are aggregated to get the final output. Finally, if the output resulted from the fuzzy rules are in the form of a fuzzy set, defuzzification interface transforms the fuzzy result into a crisp value (Shaheen 2005).

On the other, fuzzy calculus is used for performing mathematical operations on the fuzzy sets. According to the fuzzy set theory, when the inputs of any function (g) with n real arguments are in the form of fuzzy sets, the output will be a fuzzy set and can be calculated using t-norm extension principle (Equation 2.7).

$$g(A_1, \dots, A_n)(y) = \sup_{g(x_1,\dots,x_k)=y} A_1(x_1)\, t \dots t\, A_n(x_n) \tag{2.7}$$

Where, $A_1, \dots, A_n$ are membership functions defined on the input variables $x_1, \dots, x_n$ and $g(A_1, \dots, A_n)$ is membership function of the Output (Chang and Hung 2006).

A t-norm is any binary operation form $[0,1]^2$ to [0, 1] that is commutative, associative, monotonic and satisfies the boundary conditions if Equation 2.8. Minimum is an example of a t-norm operation (Pedrycz and Gomide 2007).

$$0\, t\, x = 0 \text{ and } 1\, t\, x = x \tag{2.8}$$

Another method for performing fuzzy calculus is alpha-cut method. This method is equal to the extension principal when minimum operation is used for t-norm (Chang and Hung 2006).The alpha-cut of a fuzzy set A at the level of $\propto \in (0,1]$ is a set $A_\propto$, whose members have a membership degree equal or greater than $\propto$.

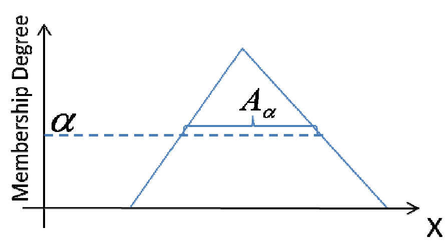


Figure 2.6 Alpha-cut of a fuzzy set A

Any fuzzy set A can be represented uniquely by infinite number of alpha-cuts. Equation 2.9 indicates how the final fuzzy set can be formed by aggregating its alpha-cuts (Pedrycz and Gomide 2007).

$$A = \cup_{\propto > 0} \propto A_{\propto} \quad \text{Or} \quad A(x) = \text{Sup}_{\propto \in (0,1]} [\propto A_{\propto}(x)] \tag{2.9}$$

Any function $Y = g(A_1, A_2, \ldots, A_n)$, where $A_1, A_2, \ldots, A_n$ are fuzzy sets, can be calculated using alpha-cut method: first, interval analysis is performed on the alpha-cuts of input parameters to find the output alpha-cuts at different levels of alpha (Equation 2.10); second, the $\propto$-cuts of Y at different levels of alpha can be aggregated to produce the fuzzy set for Y.

$$y_{\propto} = g(A_{1,\propto}, A_{2,\propto}, \ldots, A_{n,\propto}) \tag{2.10}$$

Alpha-cut method can be implemented as a computer program. Figure 2.7 indicates how this method is used for estimating the output fuzzy set of a computer model when the inputs are fuzzy sets (Figure 2.7). In each level of alpha, the output alpha-cut intervals are calculated using interval analysis. Generally, Optimization routines should be carried out for finding these intervals. However, if the model is monotonic (increasing or decreasing) with regard to the input fuzzy sets, we can calculate the output alpha-cut based on the Infimum (Inf) and Supremum (Sup) values of the input alpha-cut intervals (Abebe et al. 2000). For example, if the model is increasing with regard to all input fuzzy sets, the Inf of input alpha-cuts will generate the Inf of output alpha-cut.

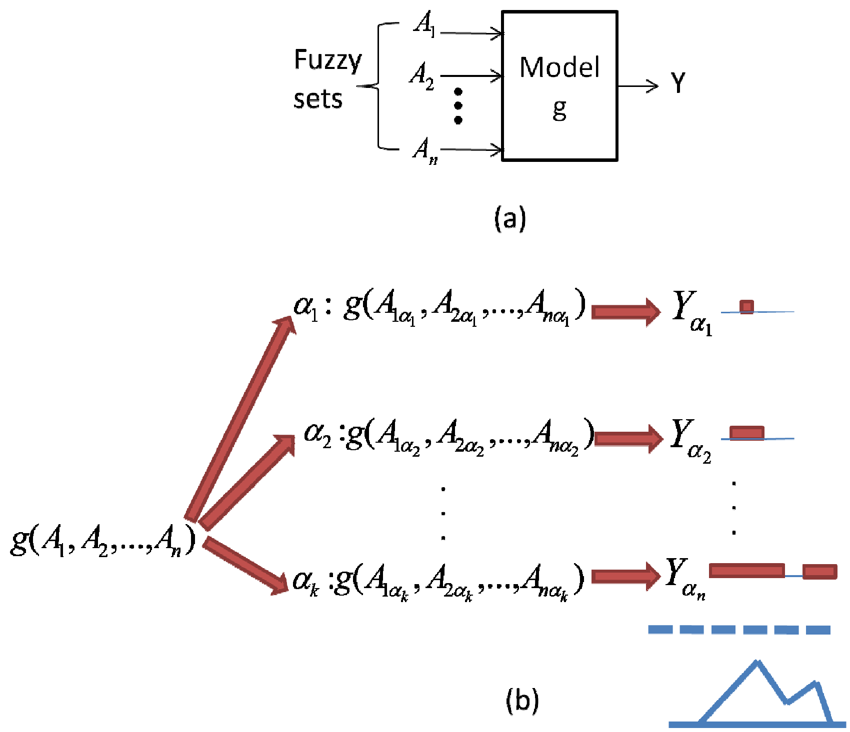


Figure 2.7 (a) A model g with input fuzzy sets. (b) Implementation of alpha-cut method on a computer model.

The ultimate goal of any risk analysis model is decision making. For making decision using the output fuzzy set, we can defuzzify the fuzzy set to get a crisp value and use that value for decision making. Centroid is one of the most common methods for defuzzification. The defuzzified value is calculated in this method by finding the center of the area under the membership function. Another method for making decision using fuzzy sets is based on the confidence level. The decision maker is able to decide on a confidence level $\propto$ and the alpha-cut of the fuzzy set is used to provide a range for the output. In this way, the decision maker can choose from a range of values instead of crisp output.

Furthermore, one can compare a fuzzy set with a threshold. For example, the possibility P that the fuzzy set A with membership function μ is less than the threshold T is calculated using Equation 2.11 (Liu 2002).

$$P(A < T) = \sup_{u<T} \mu(u) \tag{2.11}$$

2.3.1 Fuzzy Discrete Event Simulation

It is mentioned that in traditional frameworks of discrete-event simulation, the uncertainty about the duration of the events is modeled using probabilistic distributions. In fuzzy discrete event simulation this uncertainty is modeled using fuzzy sets. Recently, this approach is proposed for dealing with data deficient and subjective environments in construction projects. Many activities in construction projects can start without obeying a strict amount of resources and the decision on the activation of activities could be subjective (Zhang et al. 2003). Therefore, linguistic variables and fuzzy rules are used for expressing the quantities of resources and deciding on the activation of each activity, respectively.

Since the durations of the vents are fuzzy sets in fuzzy discrete event simulation, the simulation time can be updated using fuzzy algebraic operations. Therefore, the simulation time will be also in the form of a fuzzy set (Perrone et al. 2001). In the traditional simulation model, a crisp value is used for the events completion time, which allows scheduling of the events by a simple comparison. However, for scheduling the event list in fuzzy simulation a fuzzy ranking method is required to compare fuzzy completion times of different events.

Some studies have been done using the traditional fuzzy ranking methods for ranking fuzzy number in discrete event simulation. These approaches use defuzzication to assign the fuzzy set representing the completion time of the event to a crisp number, and then fuzzy rating will be used instead of crisp rating. Zhang et al. (2003) utilize the Height Defuzzification Method (HDM) (Bojadziv and Bojadzeiv 1997). Perrone et al. (1998) applied the Integral Value method (Liou and Wang 1992) and the Chen method (Chen 1985). Bortolan and Degani (1985) as well as Wang and Kerre (2001) presented a comprehensive survey of the available fuzzy set ranking methods. There is not a best solution for ranking fuzzy numbers (Bortolan and Degani 1985) and each solution should be evaluated within the specific decision making process (Perrone et al. 2001). By converting fuzzy numbers into crisp numbers for crisp-ranking, the fuzzy information such as subjectivity or vagueness may be lost (Yufei 1991; Bortolan and Degani 1985; Zadeh 2004). Different methods are suggested for ranking fuzzy sets without defuzzifyig the fuzzy set such as Tran and Duzkstein (2002) and Mehdi et al. (2005).

2.4 State of the Art Review in Considering both Fuzzy and Random Inputs for a Model

In previous section, simulation models that have either fuzziness or randomness in their input parameters are discussed. This section reviews the former approaches for generalized problem in which we have both types of uncertainty, fuzzy and probabilistic. Here, we have to find the output of a model (g) that $(\mathrm{R}_1, \mathrm{R}_2, \ldots, \mathrm{R}_\mathrm{n})$ being random variables and $(\mathrm{A}_1, \mathrm{A}_2, \ldots, \mathrm{A}_\mathrm{m})$ being fuzzy sets as its input parameters (Figure 2.8).

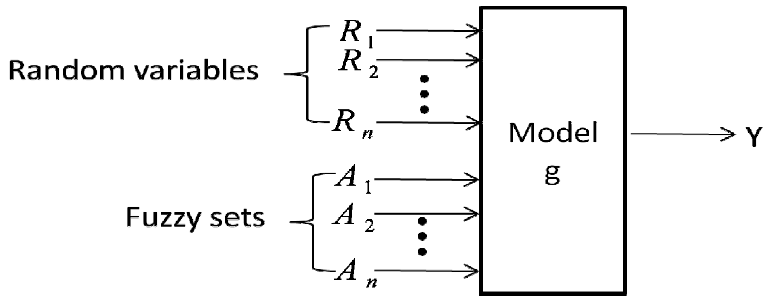


Figure 2.8 A function M with both fuzzy and random inputs

To estimate the output of this generalized model, most researchers attempt to eliminate or transform one type of uncertainty to another before performing a simulation. For example, Wonneberger et al. (1995) performed a possibility to probability transformation for a problem with both types of uncertainty. In this way, they replace input fuzzy sets by PDF to change the problem to a purely probabilistic simulation (see Figure 2.9). These transformations are questionable since fuzzy logic and probability theory capture different types of information. Therefore, there is a chance of losing information or introducing artificial knowledge that is not actually available to the model via these transformations (Guyonnet et al. 2003). Also, there is no fully accepted way of transforming one to another (Pedrycz and Gomide, 1998).

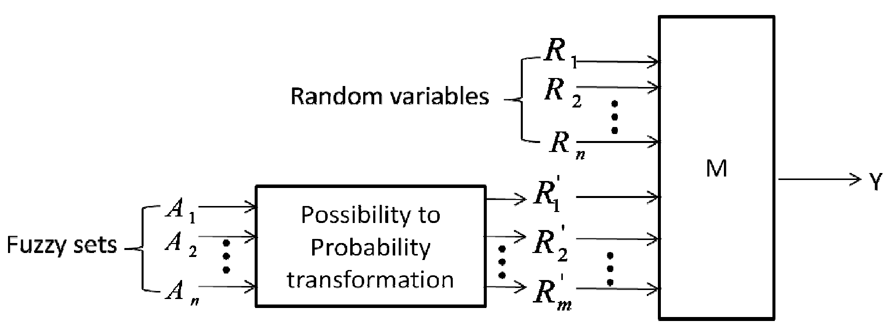


Figure 2.9 Converting fuzzy sets to PDF before performing Monte Carlo Simulation

Guyonnet et al. (2003) proposed a “hybrid approach” for solving a model that has both fuzzy and random types of uncertainty without transforming one type to another. The essence of their approach is summarized in Figure 2.10 for a model M that has both random variables as probabilistic distributions $R_1, R_2, \ldots, R_n$ and fuzzy sets $\mathrm{F}_1, \mathrm{F}_2, \ldots, \mathrm{F}_\mathrm{m}$ for the inputs. To determine the output Y of this model, as indicated in Figure 2.10, a number of sample sets (w) are generated from the probability distributions. After assigning each sample set $r_{1i}, r_{2i}, \ldots, r_{ni}$ to the random variables of the model, the $\propto$-cuts of the fuzzy inputs are calculated for different levels of alpha. Let us recall that the $\propto$-cut of a fuzzy set F at the level of $\propto \in (0,1]$ is a set $\mathrm{F}_\propto$, whose members have a membership degree equal or greater than $\propto$. Therefore, the $\propto$-cut of each fuzzy input represents a set of values. Guyonnet et al. (2003) calculated the Infimum (Inf) and Supremum (Sup) values of the model M considering all the values that are located within the $\propto$-cuts of the input fuzzy sets. In this way, for each sample set (i) and each alpha level ($\propto_j$) two output values are calculated: $Y_{i\propto_j,inf}$ and $and\; Y_{i\propto_j,Sup}$ (Figure 2.10). Guyonnet et al. (2003) suggested that minimization and maximization algorithm can be used for finding Inf and Sup values of a general model. However, in their application, the model was a simple monotonic function, and the Inf and Sup values were identified directly without using minimization or maximization algorithms.

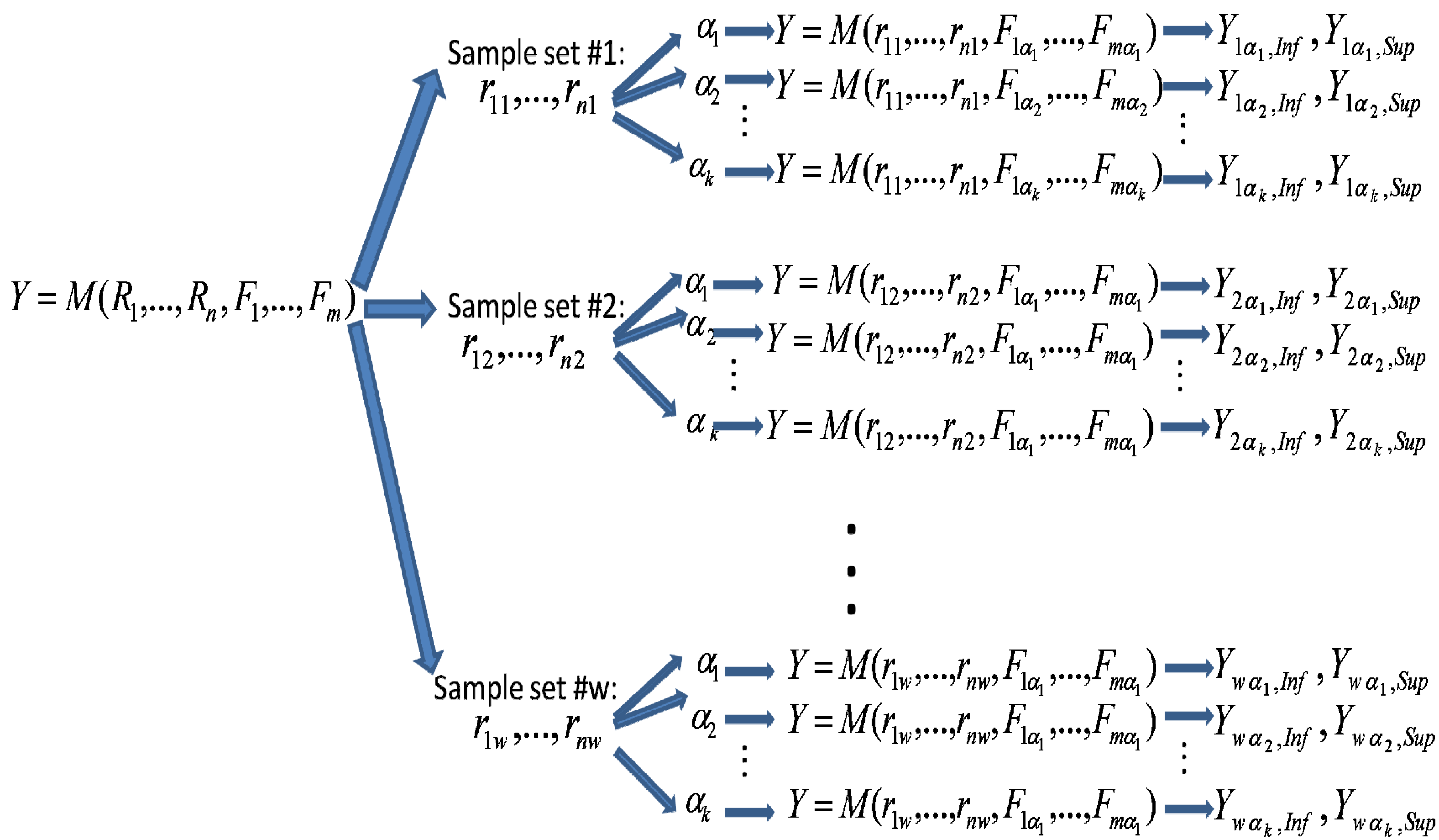


Figure 2.10 Guyonnet et al.'s (2003) "hybrid approach" for fuzzy Monte Carlo simulation

For decision making based on the hybrid approach, Guyonnet et al. (2003) developed the histograms of the Inf and Sup values of the alpha-cuts at each alpha-level and calculated the final Inf and Sup of the output alpha-cut based on a 5% probability of getting respectively lower and higher values. The alpha-cuts are then aggregated to produce the output as a fuzzy set (Figure 2.11). In their application, they were interested in comparing the output fuzzy set with a specific threshold. They perform this comparison by finding the possibility that the output fuzzy set be less that the required threshold.

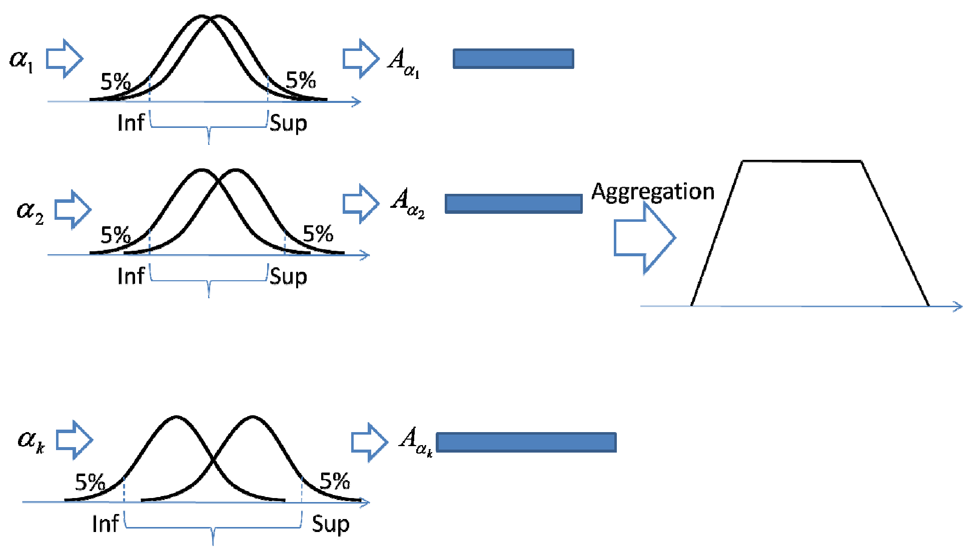


Figure 2.11 Calculating the output alpha-cut based on the histogram of the Inf and Sup values of the alpha-cuts at the level of α

The approach of Guyonnet et al. (2003) is unique in considering fuzzy and probabilistic simultaneously in Monte Carlo simulation; however, it is not free from shortcomings. A careful analysis reveals some points of the approach which require further evaluation/refinement.

a) The alpha-cuts of a fuzzy set cannot always be represented by Inf and Sup values. Therefore, considering only Inf and Sup values of the alpha-cuts may decrease the specificity of the results, since we may consider intervals that do not actually belong to the output alpha-cut in our results (Figure 2.12(b)).

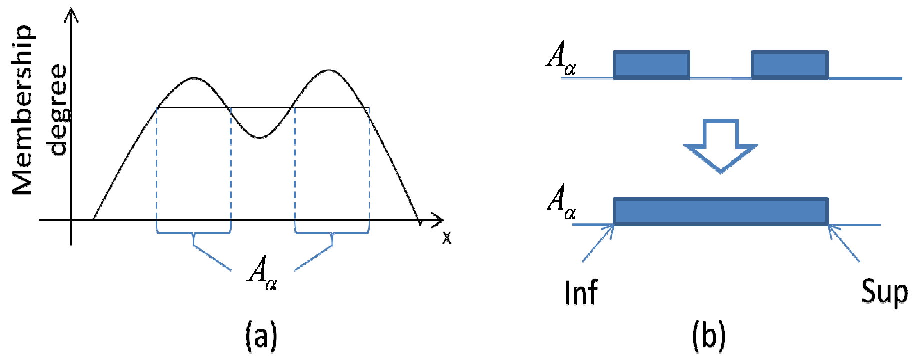


Figure 2.12 (a) An alpha-cut of a non-convex fuzzy set (b) Considering only Inf and Sup values of the alpha-cuts and the associated lack of specificity

b) Guyonnet et al. (2003) do not mention why a 5% probability of getting lower and higher values of the histograms of the alpha-cuts will generate the Inf and Sup of the output alpha-cut. In this manner, they remove the random type of uncertainty and consider a fuzzy set for the output. Buardit et al. (2005) indicate this method leads to unrealistic output and overestimation.

c) In addition, if only random inputs are considered as the extreme case for this model, the result will not be similar to the traditional Monte Carlo simulation approach. In this case, the absence of fuzziness results in equal histograms for the Inf and Sup values at all levels of alpha. Therefore, the method will produce the same alpha cuts for all values of alpha, and the result of their aggregation will be an interval that does not contain enough probabilistic or fuzzy information to help in decision making.

Baudrit et al. (2005) propose an approach for “post-processing” of the hybrid method of Guyonnet et al. (2003) using the theory of evidence (or theory of belief functions; see Shafer 1979). The final output of their proposed method does not directly represent the fuzziness or randomness, but rather analyzes the output with concepts that are defined in the theory of evidence.

2.5 Conclusions

This chapter, first, discussed computer models in which either randomness or fuzziness exist in their input parameters. It is indicated that each of these models follow different mathematical logic. The main reason is that fuzzy logic and probability theory have conceptual difference; while calculating a probability value deals with “occurrence of events”, fuzzy logic deals with graduality concept and has nothing to do with frequencies of an event (Pedrycz 1998). Furthermore, the methods for making decision based on random variable and fuzzy set are totally different. As a result, having both fuzziness and randomness in the input parameters of a computer simulation model brings controversial issues. Literature suggests two main approaches for finding the output of such models: 1) transforming one type of uncertainties to another before processing the model, and 2) keeping the uncertainties as their original forms while processing the model. As we discussed in the chapter, transformations of fuzzy sets to PDFs or vice versa are questionable and there is no fully accepted way of transforming one by another. Furthermore, even in the second approach, the output is analyzed by considering only one type of uncertainty or by representing fuzziness and randomness in other forms based on the theory of evidence.

Since subjectivity and lack of data usually exist in some of the parameters affecting a construction project, a reliable framework that can address both types of randomness and fuzziness in the inputs of a model can enhance modeling of construction projects. However, the use of such models in construction management is very limited which could be due to the limitations of available methods, and because these methods are fairly new and are not yet introduced to construction managers. This thesis proposes a fuzzy Monte Carlo simulation framework that can accept both fuzzy and probabilistic inputs for risk analysis of construction projects. In the proposed framework, random and fuzzy uncertainties are represented explicitly in the output to allow the decision maker completely understands the origins of each type of uncertainty and make the wise decision based on the conceptual difference of fuzziness and randomness.

CHAPTER 3 - FUZZY MONTE CARLO SIMULATION (FMCS)

3.1 Introduction

This chapter proposes Fuzzy Monte Carlo Simulation (FMCS) framework for risk analysis of construction projects. This framework is a generalized form of Monte Carlo simulation in which we can have both fuzzy and probabilistic distributions for the inputs of construction simulation models.

The FMCS framework, which includes the approach for performing simulation and analyzing the output results, is explained in Section 3.2. Section 3.3 discusses the practical aspects of applying FMCS on construction projects. It also provides a cost range estimating template to show how FMCS can be implemented for practical use in construction management. Section 3.4 provides a comparison between FMCS framework and traditional Monte Carlo simulation through an illustrative example. Finally, Section 3.4 summarizes the contributions of this chapter.

3.2 Proposed Approach

A simulation based approach for risk analysis of a problem in construction management can be summarized in the following steps: (1) identifying the structure of the problem (2) quantifying uncertainty in different parameters of the model (3) performing a simulation (4) analyzing the results and making decision (Walls III and Smith 1998). Monte Carlo simulation is a common simulation approach that is performed in construction management. In Monte Carlo simulation, all the input uncertainties are modeled based on probability theory (Figure 3.1(b)), and random sampling of inputs is performed to find the output results. However, since the sources of information about various parameters of a project differ, we may have probabilistic uncertainty for some of the input variables and fuzzy uncertainty for others. Therefore, a simulation method is required that is capable of handling both types of fuzzy and probabilistic inputs. Fuzzy Monte Carlo Simulation (FMCS) is proposed as a solution to this problem in this research. FMCS is a generalized form of Monte Carlo simulation that provides the capability of using both fuzzy logic and probability theory for quantifying the input uncertainties of a Monte Carlo simulation model (Figure 3.1(a)).

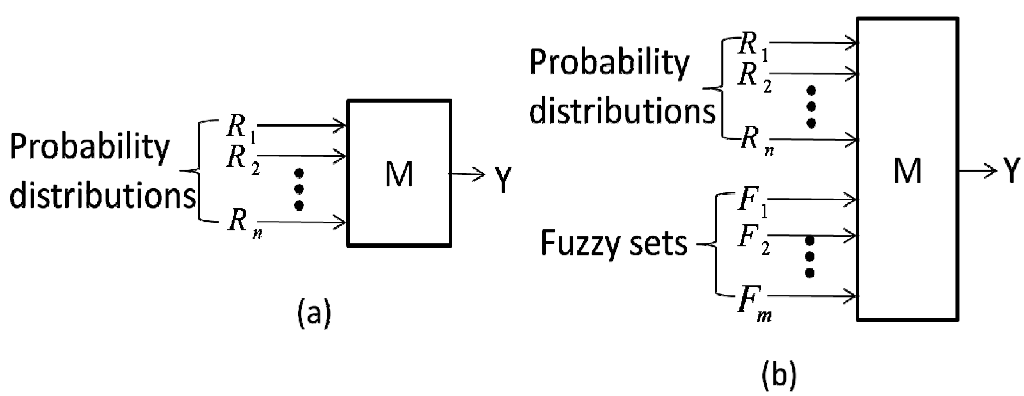


Figure 3.1 (a) Traditional model for Monte Carlo simulation with random inputs (b) FMCS model as a generalized form of Monte Carlo Simulation

FMCS integrates fuzzy arithmetic method with Monte Carlo simulation to find the output of a model with both fuzzy and probabilistic inputs, Consider a model (M) that has both random variables as probabilistic distributions $R_1, R_2, \dots, R_n$ and subjective variables as fuzzy sets $F_1, F_2, \dots, F_m$ for the inputs (Figure 3.1(b)). In the FMCS framework, sample sets are produced from the probabilistic distributions. After assigning each sample set $r_{1i}, r_{2i}, \dots, r_{ni}$ to the random variables of the model, the model will contain only fuzzy input variables. Fuzzy arithmetic is used to calculate the output in the form of a fuzzy set (Figure 3.2).

As discussed in chapter 2, based on the extension principle (Zadeh 1975), one can apply fuzzy arithmetic on a function (M) with input fuzzy sets $\mathrm{F}_1, \mathrm{F}_2, \dots, \mathrm{F}_\mathrm{n}$ to get the output fuzzy set Y. The α-cut method can also be used to perform fuzzy arithmetic on a function. This method is equivalent to the Zadeh's extension principle. However, it is easier to implement since it is based on interval analysis of the α-cuts of the input fuzzy sets.

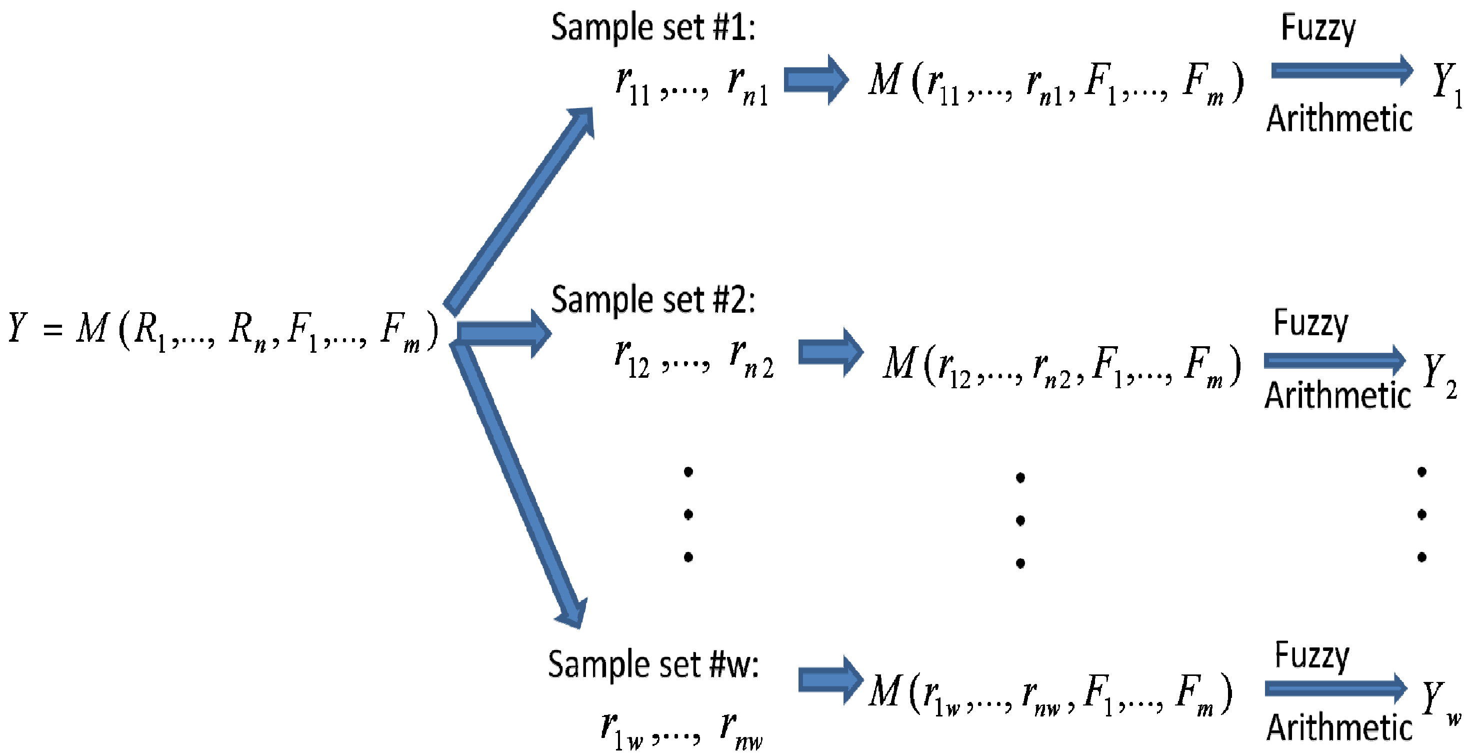


Figure 3.2 Fuzzy Monte Carlo Simulation (FMCS) approach

Since in FMCS, fuzzy arithmetic is performed for each sample set, the output of FMCS is represented as a number of fuzzy sets with random variation. This randomness is resulted from random samplings of random input parameters. .The output can be modeled with a fuzzy random variable. A fuzzy random variable is a mapping from the probability space to the fuzzy sets (Terán 2007). Figure 3.3 illustrates how each sample set of probability space is mapped to a fuzzy set.

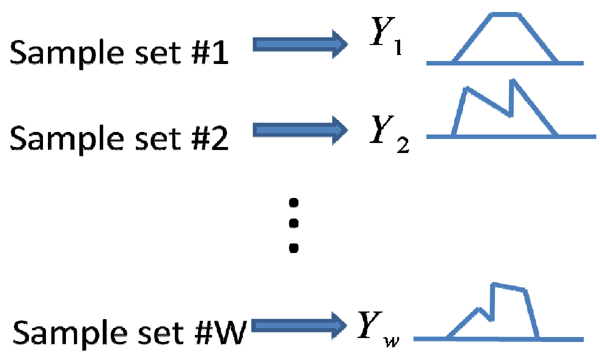


Figure 3.3 In FMCS, each sample set of probability space is mapped to a fuzzy set

3.2.1 Output Analysis of FMCS Framework

The ultimate goal of any risk analysis model is decision support. FMCS is proposed as a general form of Monte Carlo simulation and similar decisions that are made using Monte Carlo simulation can be made based on the FMCS framework. The mean and variance can be calculated to provide an estimate of the output of Monte Carlo simulation. We can benefit from work in measurement theory for calculating the mean and variance of the output of the FMCS framework. Terán (2007) used fuzzy random variables to represent the results of measurements. He represented each measurement as a fuzzy set, while the variability between fuzzy sets was considered random. This scenario is similar to results obtained from fuzzy Monte Carlo simulation. Terán (2007) suggested to use fuzzy arithmetic for performing statistical calculations on the fuzzy samples. Similarly, we can apply fuzzy arithmetic to the fuzzy outputs of FMCS to find the mean and variance. For example, Equation 3.1 indicates how Zadeh's (1975) extension principle can be used to find the membership function of mean, A_{mean}, of the outputs of FMCS, $Y_1, Y_2, \dots, Y_w$, with membership functions $A_1, \dots, A_w$.

$$A_{mean}(y) = Sup_{y=\frac{\sum_{i=1}^{w} y_i}{w}} (\mathrm{A_1(y_1)}, \dots, \mathrm{A_w(y_w)}) \tag{3.1}$$

When we have no fuzziness, the values $Y_1, Y_2, \dots, Y_w$ are real numbers and the results of the extension principle will be the same as the result of performing normal arithmetic on crisp numbers. In this sense, this approach provides an analysis tool that behaves reasonably well.

However, the mean and variance is not enough for the risk analysis of construction projects. In construction management, a decision-maker is usually interested in two other important statistics: (1) an arbitrary quantile, and (2) the probability of exceeding (or not exceeding) a specific threshold. For example, one may want to estimate the completion time of a project with 95% confidence. This value is referred as the 95th quantile of the output. In the context of the simulation process, this means that 95% of the conducted simulation results are less than the completion time. Decision-makers are also interested in finding the probability that a project will exceed a certain value of cost or time (Ahuja et al. 1994).

The Cumulative Distribution Function (CDF) is typically used for finding the probability of not exceeding a given threshold. Equation 3.2 defines the CDF function of a random variable X (Ahuja et al. 1994). The inverse of the CDF is used for finding the arbitrary quantile.

$$\mathrm{F_X}(\mathrm{x}) = \Pr\{\mathrm{X} < x\} \tag{3.2}$$

Considering a finite number of random samples resulting from a Monte Carlo simulation, the CDF function can be estimated from Equation 3.3.

$$F_X(t) = \frac{Number\ of\ samples\ that\ are\ less\ than\ t}{Total\ number\ of\ samples} \tag{3.3}$$

However, the samples of the output of a FMCS are fuzzy sets, and when the threshold is a member of a sample fuzzy set, there is an uncertainty in considering the sample fuzzy set as less than or greater than the threshold t (Figure 3.4).

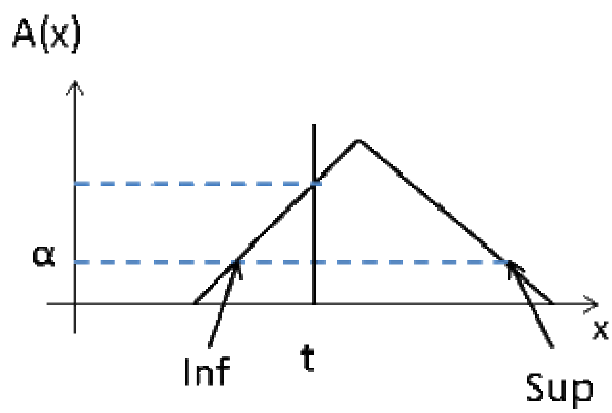


Figure 3.4 The threshold is in the sample fuzzy set

This problem is solved by incorporating fuzziness into the CDF and generating a fuzzy CDF. The Inf and Sup values of the α-cuts of the samples are used to calculate two CDFs at each α-level. The number Inf value of the alpha-cuts that are less than a threshold are greater than or equal to the number of Sup values that are less than that threshold. Therefore, $F_{\propto,max}$ is calculated based on the Inf values of the α-cuts of the samples at the level of α (Equation 3.4), and $F_{\propto,min}$ is calculated by considering the Sup values of the $\propto$-cuts of the samples at the level of $\propto$ (Equation 3.5). For example, in Figure 3.4, the fuzzy set A is considered less than t for calculating $F_{\propto,max}(t)$, and is considered greater than t for calculating $F_{\propto,min}(t)$.

$$F_{\propto,max}(t) = \frac{Number\ of\ Inf\ of \propto -cuts\ of\ the\ samples\ that\ are\ less\ than\ t}{Total\ number\ of\ samples} \tag{3.4}$$

$$F_{\propto,min}(t) = \frac{Number\ of\ Sup\ of \propto -cuts\ of\ the\ samples\ that\ are\ less\ than\ t}{Total\ number\ of\ samples} \tag{3.5}$$

$F_{\propto,max}(t)$ and $F_{\propto,min}(t)$ should be calculated for various values of t between minimum sample and maximum sample, in order to develop the CDF graphs of $F_{\propto,min}$ and $F_{\propto,max}$. $F_{\propto,min}$ and $F_{\propto,max}$ will generate a CDF bound $F_{\propto}(x)$ at each alpha level. The CDF bound represents a range for CDFs at an alpha level (Figure 3.5).

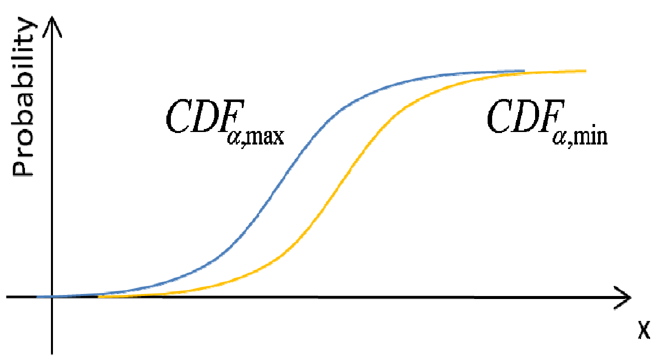


Figure 3.5 CDF bound represents a range of CDFs in an alpha level

The final fuzzy CDF, $F(x)$, can be determined by aggregating CDF bounds at different levels of alpha based on the representation theorem (Equation 3.6; Pedrycz and Gomide 2007).

$$F(x) = Sup_{\propto \in [0.1]}[\propto F_{\propto}(x)] \tag{3.6}$$

Since fuzzy CDF, $F(x)$, represents both probability and membership degree for the outputs of FMCS,the graphical representation of fuzzy CDF is in the form of a 3-Dimentional(3D) graph Figure 3.5(a) represents the CDF bounds that are used to produce the 3D graph of the fuzzy CDF in Figure 3.6(b). The 2-Dimentional (2D) graph of Figure 3.6(b) is represented in Figure 3.6(c). In this figure we can see how CDF bounds produce different layers of fuzzy CDF.

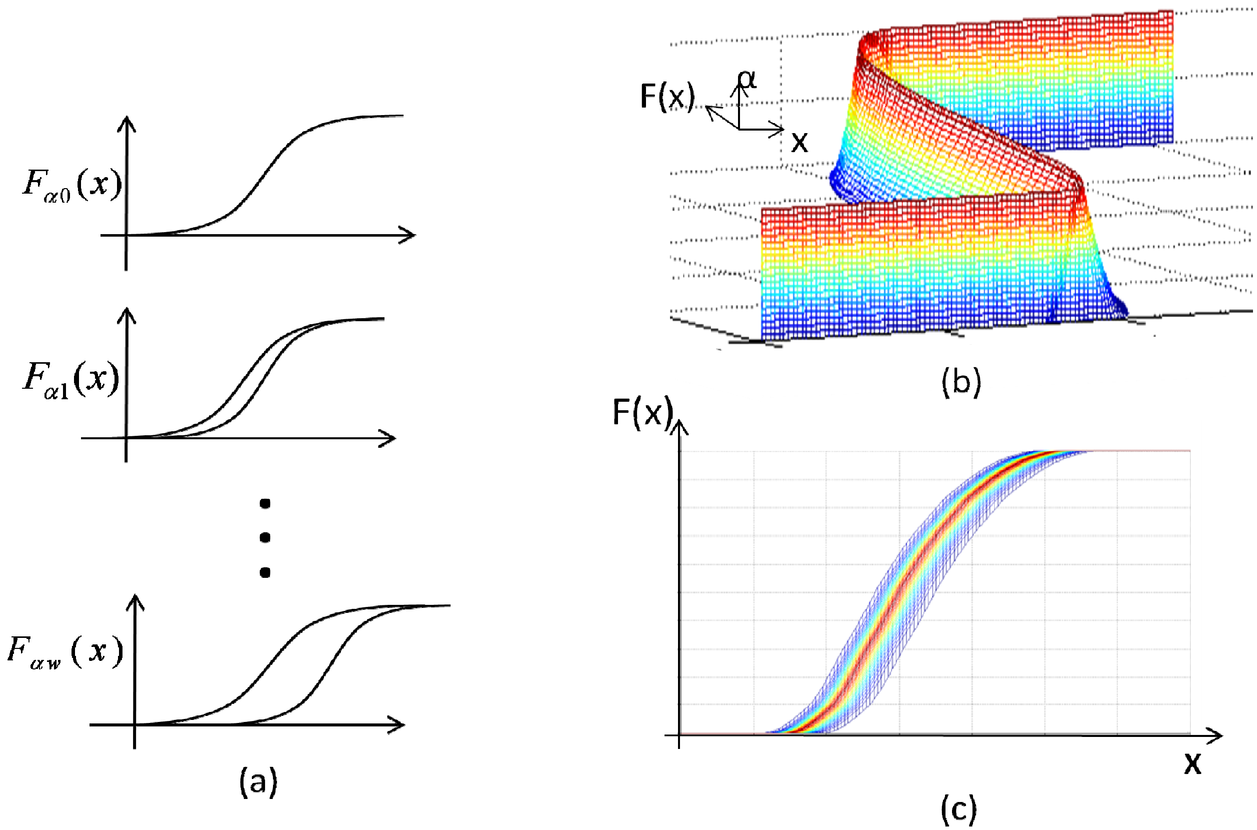


Figure 3.6. (a) CDF bounds at different levels of alpha to generate the fuzzy CDF (b) fuzzy CDF resulted from aggregating CDF bounds (c) 2D view of the fuzzy CDF in (b)

Fuzzy CDF provides the capability of representing both fuzzy and probabilistic uncertainty in a single figure as the output of FMCS framework. Furthermore, when we have no fuzziness, each sample value is a real number instead of a fuzzy set. In this case, $F_{\propto,max}(x)$ equals to $F_{\propto,min}(x)$, and all of the alpha levels will have equal CDFs. Therefore, the results are exactly equal to those obtained by traditional Monte Carlo simulation. This behavior of FMCS framework is also illustrated in section 3.4 using an illustrative example. However, Fuzzy CDF has a shortcoming in that only the Inf and Sup values of the α-cuts are considered for decision making, while the alpha-cuts of a fuzzy set cannot always be represented by the Inf and Sup values. This issue is an area for future research.

Having developed the fuzzy CDF, we can perform any decision analysis that can be performed using CDF. The estimator can find the probability that the output is less than a threshold t. The answer is in the form of a fuzzy set that is obtained by intersecting the fuzzy CDF graph at the desired threshold. A method for making decision using fuzzy sets is based on the confidence level. The estimator is able to decide on a confidence level between 0 and 1 to get a range of values for the final output. This range is calculated by finding the α-cut at the value of 1 minus the confidence level (Mauris et al. 2001). In this way, the estimator can choose from a range of values instead of a crisp output. An arbitrary quantile can also be estimated using the inverse of the fuzzy CDF. Section 3.4 compares decision making using Fuzzy CDF resulting from FMCS framework with CDF resulting from traditional Monte Carlo simulation through an example.

3.3 Practical Aspects of Using FMCS in Construction Risk Assessment

One can find many practical examples in Monte Carlo simulation of construction projects in which some of the input variables are estimated based on experts' judgments and some are derived from historical data. FMCS is appropriate in these situations since it can solve a model in which experts' judgments are represented using fuzzy sets and historical data are used to develop probability distributions of input parameters.

For example, for life-cycle analysis of a pavement design, Walls III and Smith (1998) used recent bid records to find probability distributions of the costs of construction and rehabilitation of a project, while experts' judgment has been used for estimating the service life of the pavement. Monte Carlo simulation is used as the method of risk analysis in this study. Although explaining the details of this project is beyond the scope of this research, we suggest this work can be used as an actual case study of FMCS framework for future research.

Range estimating includes a wide range of examples in which FMCS can be applied. Range estimating using Monte Carlo simulation is a common process for risk analysis and decision making regarding the budget and schedule of construction projects. The approach is based on considering the Work Breakdown Structure (WBS) of a project and estimating the cost or duration of each work package in the form of a probability distribution function. The Monte Carlo simulation method is used to aggregate the work packages and to estimate the range and degree of uncertainty for the overall project cost or duration (Shaheen et al. 2007; Ahuja et al. 1994).

Expert judgment has been extensively used in the literature for estimating the uncertain input values of the cost or schedule range estimating models of construction projects. Ayyub and Haldar (1984) used fuzzy logic to incorporate the effect of subjective factors on the duration of construction activities. Their approach is used by AbouRizk and Sawhney (1992) for range estimating of the duration of construction projects. As an example, cost range estimating is studied in more details. Accurate cost estimation plays a major role in the success of a construction project. Different methods have been suggested in the literature for estimating the cost of construction projects (e.g. Adeli and Wu 1998) and for determining a contingency value (Touran 2003). Contingency is the anticipated cost for unknowns that may increase the total cost of a project (Ahuja et al. 1994). Monte Carlo simulation is a common approach that is performed for estimating the cost and contingency. The process of Monte Carlo simulation for cost range estimating can be summarized as the follows:

1. Provide the WBS and remove work packages that do not have major effects on the total cost of the project. Ahuja et al. (1994) suggest that those work packages that affect the total cost of the project with at least 0.5% should be considered major.
2. Provide the quantity and unit cost related to each work package. Use a PDF to represent the uncertainty associated with different values of the quantity and unit cost of each work packages.

3. Use Monte Carlo simulation to determine the uncertainty associated with the total cost of the project.

Although expert judgment is usually used in range estimating of construction projects, only the random type of uncertainty can be considered using this approach. Experts' judgment is especially useful in the preliminary stages of a project when not enough data are available for many factors. For example, before performing geotechnical tests, experts may estimate the geotechnical parameters to calculate the cost of the project. In the later stages of the project, we may still have some fuzzy parameters due to the unique aspects of the project, lack of data or subjectivity. Shaheen et al. (2007) suggested an alternative method of using fuzzy set theory for modeling uncertainties in range estimating problems. The researchers proposed a range estimating model that uses fuzzy arithmetic to estimate the cost or duration of a project with purely fuzzy inputs. The FMCS framework can be used to solve this problem by using the PDF to represent random uncertainty and fuzzy sets for representing subjective or linguistically expressed values in the WBS. A cost range estimating template is developed based on FMCS framework. This template illustrates how the FMCS framework can be implemented for practical use in construction management.

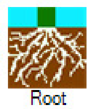
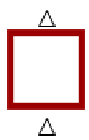
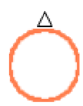
3.3.1 Fuzzy Monte Carlo Cost Range Estimating Template

A Special Purpose Simulation (SPS) template has been developed by connecting the Simphony.NET© platform and MATLAB for range estimating based on the proposed FMCS. Simphony.NET© is a simulation software application for construction processes that is capable of developing different SPS templates. The

SPS template provides a tool for an expert, who is not necessarily knowledgeable in simulation, to develop a simulation model in the area of his/her expertise (Hajjar and AbouRizk 1999). Our developed cost range estimating SPS template allows the user to represent the WBS of a project by dragging and dropping the elements on a computer screen and connecting them according to the structure of the WBS. Using the fuzzy Monte Carlo cost range estimating template, input values can be entered as the properties of each element in the form of fuzzy sets or probabilistic distributions.

The α-cut method is used to perform fuzzy arithmetic on the fuzzy sets in FMCS. Since the calculations for cost range estimating are limited to addition and multiplication, which are monotonically increasing, finding the Inf and Sup values of the output α-cut intervals is straightforward by using the Inf and Sup of the input α-cut intervals. The elements of the developed template are listed in Table 3.1. The Root element is responsible for calculating the value of alpha and deciding whether a minimum or maximum value of the α-cut should be calculated in each run of the simulation. Other elements identify their appropriate actions based on the status of the root element in each run. The cost of each child work package is calculated by multiplying its unit cost and quantity. A number of child work packages or parent work packages may be defined under a parent work package. Therefore, it is possible to have any number of levels in the WBS. The cost for the parent work package is the sum of the costs of its lower level work packages multiplied by the quantity of the parent work package. The Analysis element collects the output results and sends them to a MATLAB routine. In this routine Fuzzy CDF graph is created for decision making.

Table 3.1 Elements of fuzzy Monte Carlo cost range estimating template

Element Name	Graphical representation	Description
Root		This element defines the status of the simulation and controls the actions of all the other elements.
Parent Work Package		Parent Work Package represents a group of work packages that will be defined under this element.
Child Work Package		Child Work Package represents the lowest level of the WBS, the unit cost and quantity can be defined for this element.
Analysis Element		This element collects the outputs and calculates the statistics.

3.4 An Illustrative Example to Compare Monte Carlo Simulation and FMCS

This section analyzes the behavior of FMCS framework in comparison with Monte Carlo simulation using a cost range estimating example. A sample application by Ahuja et al. (1994) of a cost range estimating problem for a highway overpass project is used for this purpose. The unit cost and quantity for major work packages of this project are shown in Table 3.2. Probabilistic distributions are used to express the uncertainty regarding those variables. These uncertainties may result from uncertainty regarding the accuracy of take-off values or different scenarios that may happen in the field during construction. For example, uncertainty in the unit cost may be a result of uncertainty associated with the productivity of workers or variability in weather conditions. Ahuja et al. (1994) used subjective judgment to derive the given probabilities, and it is beyond the scope of this research to verify these distributions, which are also specific to this example and its assumptions. It is assumed that the model is developed correctly and their suggested probability values are appropriate. This assumption does not bring any limitations to our analysis, since the model is used with the sole goal of performing a sensitivity analysis on the FMCS framework and comparing the results with the probabilistic approach. Figure 3.7 illustrates the model developed for this example using the fuzzy Monte Carlo cost range estimating template.

Table 3.2 Major work packages and their associated cost and quantity for a highway overpass project (adapted from Ahuja et al. 1994)

Work Package	Quantity	Unit Cost
1. Excavation (m^3)	Uniform(2200, 2500)	Triangular(10, 11, 13)
2. Backfill (m^3)	Uniform(1700, 2200)	Triangular(9, 10, 13)
3.Pilings and Bells		
Piling(300 dia) (m)	Constant(160)	Constant(29)
Piling(750 dia) (m)	Constant(510)	Triangular(175, 183, 190)
Bells(1500 dia) (ea)	Constant(42)	Triangular(370, 390, 420)
Bells(1200 dia) (ea)	Constant(16)	Constant(340)
4. Cast in place concrete		
Pier footing (m^3)	Constant(73)	Triangular(320, 330, 350)
Pier column (m^3)	Constant(55)	Triangular(600, 650, 700)
Abutments (m^3)	Constant(635)	Triangular(200, 235, 290)
Approach slabs (m^3)	Constant(55)	Triangular(220, 230, 400)
Bridge girder (m^3)	Constant (1310)	Triangular(370, 390, 450)
Parapets incl. finish (m)	Constant (171)	Triangular(150, 160, 175)
Concrete median (m)	Constant(67)	Constant(124)
5. Concrete slope protection (m^3)	Uniform (1000, 1100)	Triangular(42, 45, 50)
6. Hot mix asphaltic concrete paving (m^2)	Constant (1900)	Triangular(17, 18, 19)
7. Deck water proofing	Uniform(1800, 2000)	Constant(5.7)
8. Class 5 finish (NIC parapets) (m^2)	Constant(565)	Constant(6)

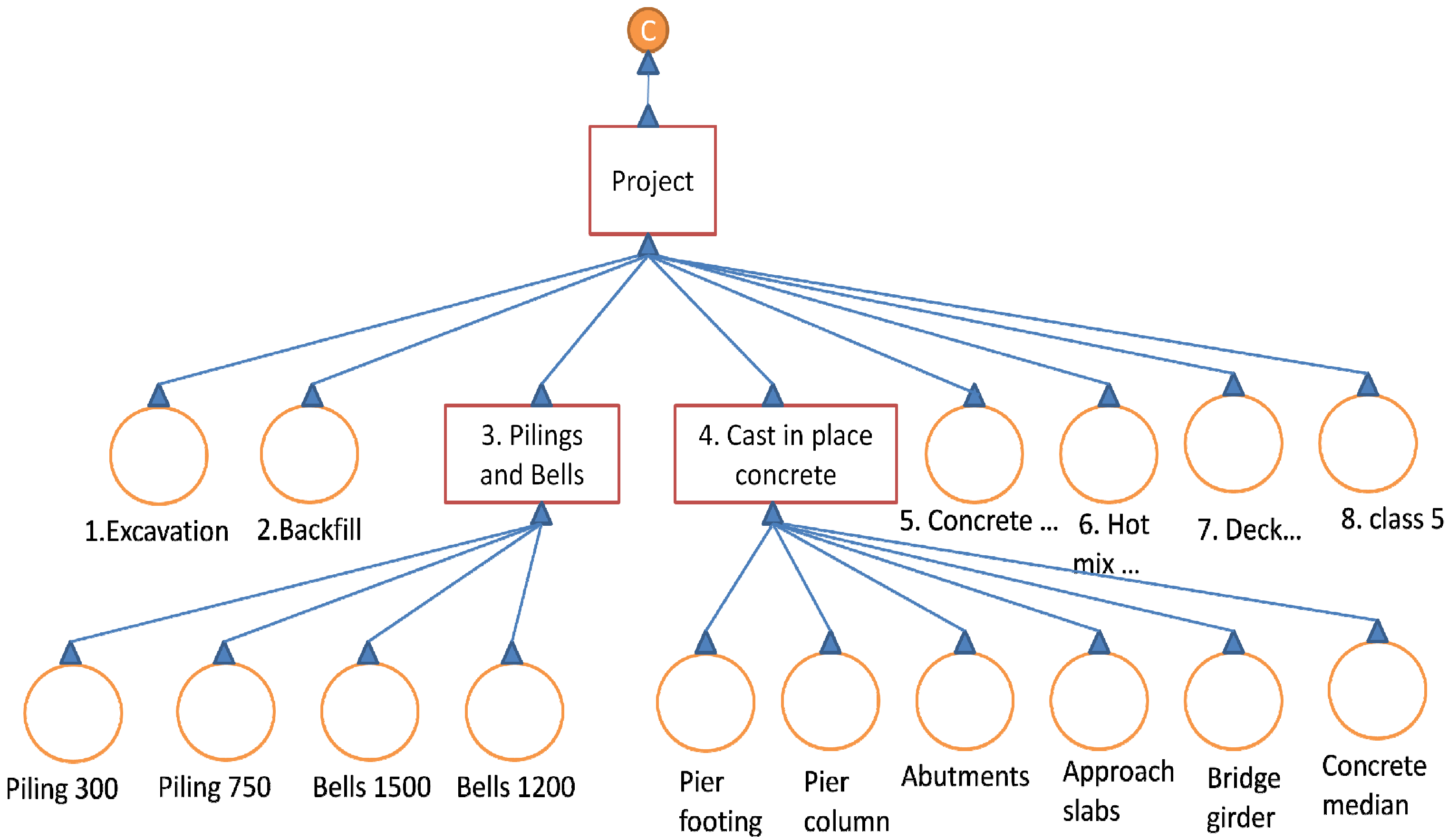


Figure 3.7 Developed model for the highway overpass example using fuzzy Monte Carlo cost range estimating SPS template

To experiment with the FMCS approach using a combination of fuzzy and probabilistic inputs, some of the probability distributions of Table 3.2 are transformed into fuzzy sets using the probability-possibility transformation method of Dubois et al. (2004). For example, Figure 3.8 represents the transformation of the triangular distribution for the unit cost of the excavation process in Table 3.2 to a fuzzy membership function based on Dubois et al. (2004). In this method, the confidence level of the intervals is estimated using the probability of that interval. This probability is equal to the area under the Probability Distribution Function that is bounded within that interval. Among different intervals of the same confidence level, Dubois et al. (2004) proved that the most informative interval is the one with minimal length, and this interval should be considered as the ∝-cut of the final fuzzy set. This approach will produce a nested family of intervals that are considered as the ∝-cuts of the final fuzzy set.

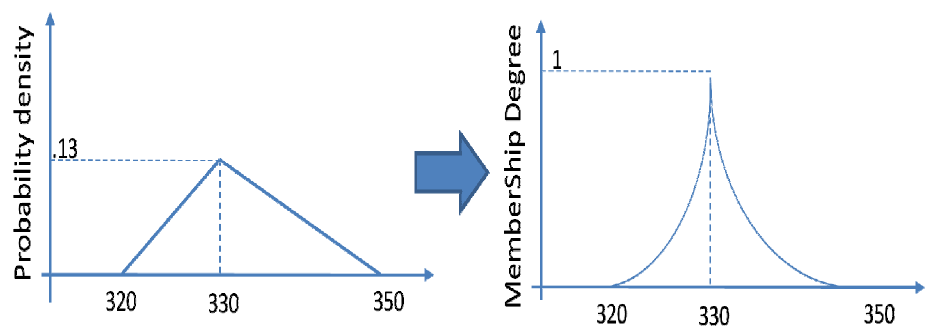


Figure 3.8 Transformation of the triangular distribution for the unit cost of the excavation process to a fuzzy membership function

It is not recommended that such transformations from probabilistic to fuzzy sets be done in practice but rather that the fuzzy sets be derived directly (e.g. form expert judgment). However, these transformations are performed in this study only to be able to compare the FMCS framework with traditional Monte Carlo simulation.

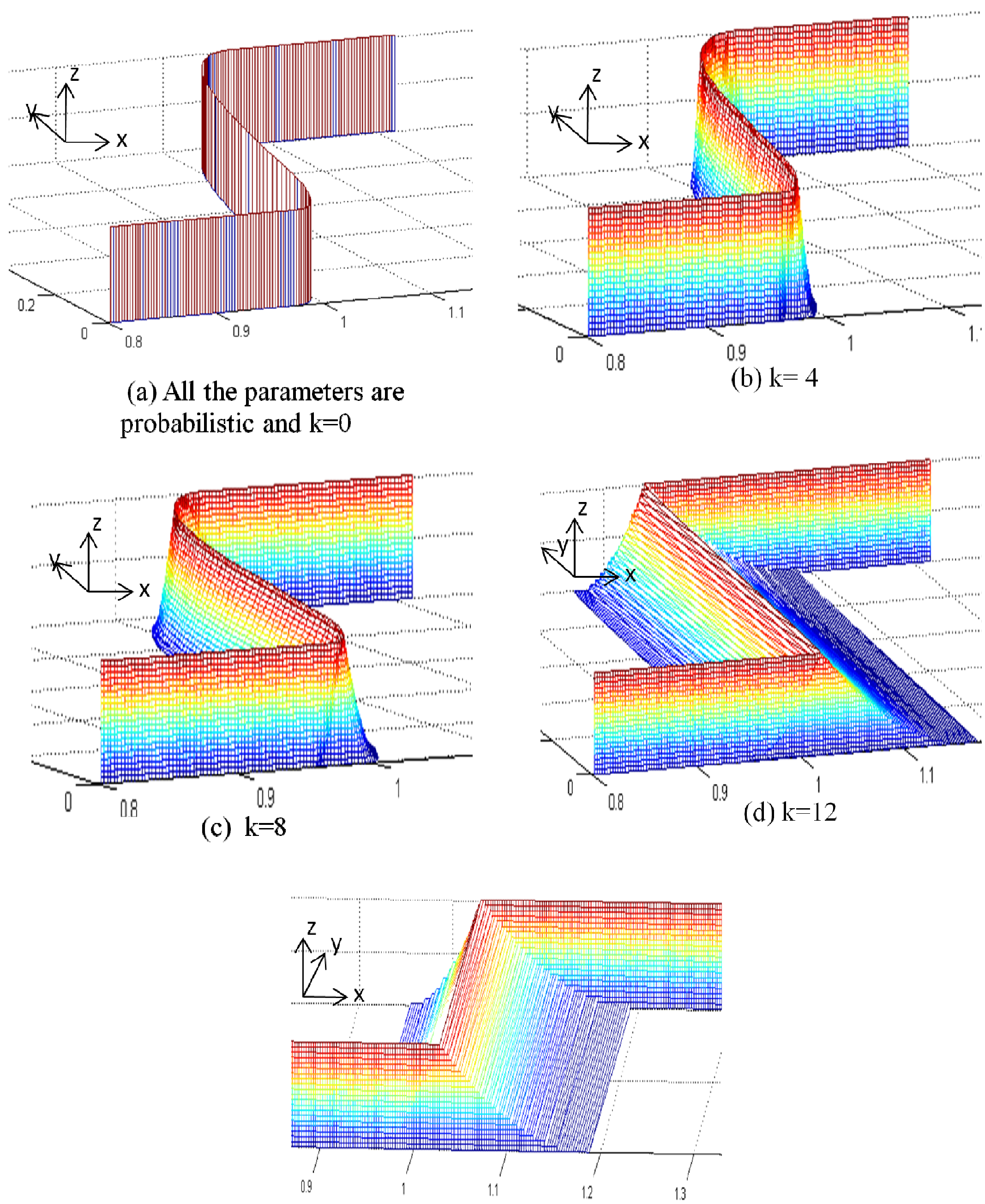
In Section 3.4.1, a sensitivity analysis is performed to investigate the effect of different numbers of fuzzy sets on the output of the FMCS framework. Section 3.4.2 discusses how similar decisions that can be made using Monte Carlo simulation can be made based on the FMCS framework.

3.4.1 Sensitivity Analysis of the FMCS Framework

For experimenting with differing numbers of fuzzy sets as inputs to the FMCS framework, the first k uncertain variables are selected from Table 3.2, which are not constant, and are transformed into fuzzy sets, while keeping the rest of the inputs as probabilistic distributions. For example, when k equals 4, the unit cost and quantity of the excavation and backfill processes are transformed into fuzzy numbers, since these parameters comprise the first four uncertain parameters in Table 3.2. The value of k is gradually increased in each experiment. The total number of uncertain variables in Table 3.2 is 16; therefore, when k equals 16, all of the uncertainty is in the form of fuzzy numbers, and we have no randomness in the model. Other variables are constant and are considered as crisp values in the model.

Figure 3.9 illustrates the 3D graphs of the fuzzy CDFs that are generated by MATLAB for several experiments performed using the FMCS framework. The x-axis indicates the total cost of the model in millions of dollars, the y-axis is the probability, and the z-axis is the alpha value associated with each output.

Therefore, these graphs illustrate both probabilistic and fuzzy uncertainty. We can see how the fuzziness of the output increases when the number of fuzzy inputs (k) increases, illustrating the intuitively appealing behavior of the method.



(a) All the parameters are probabilistic and k=0

(b) k= 4

(c) k=8

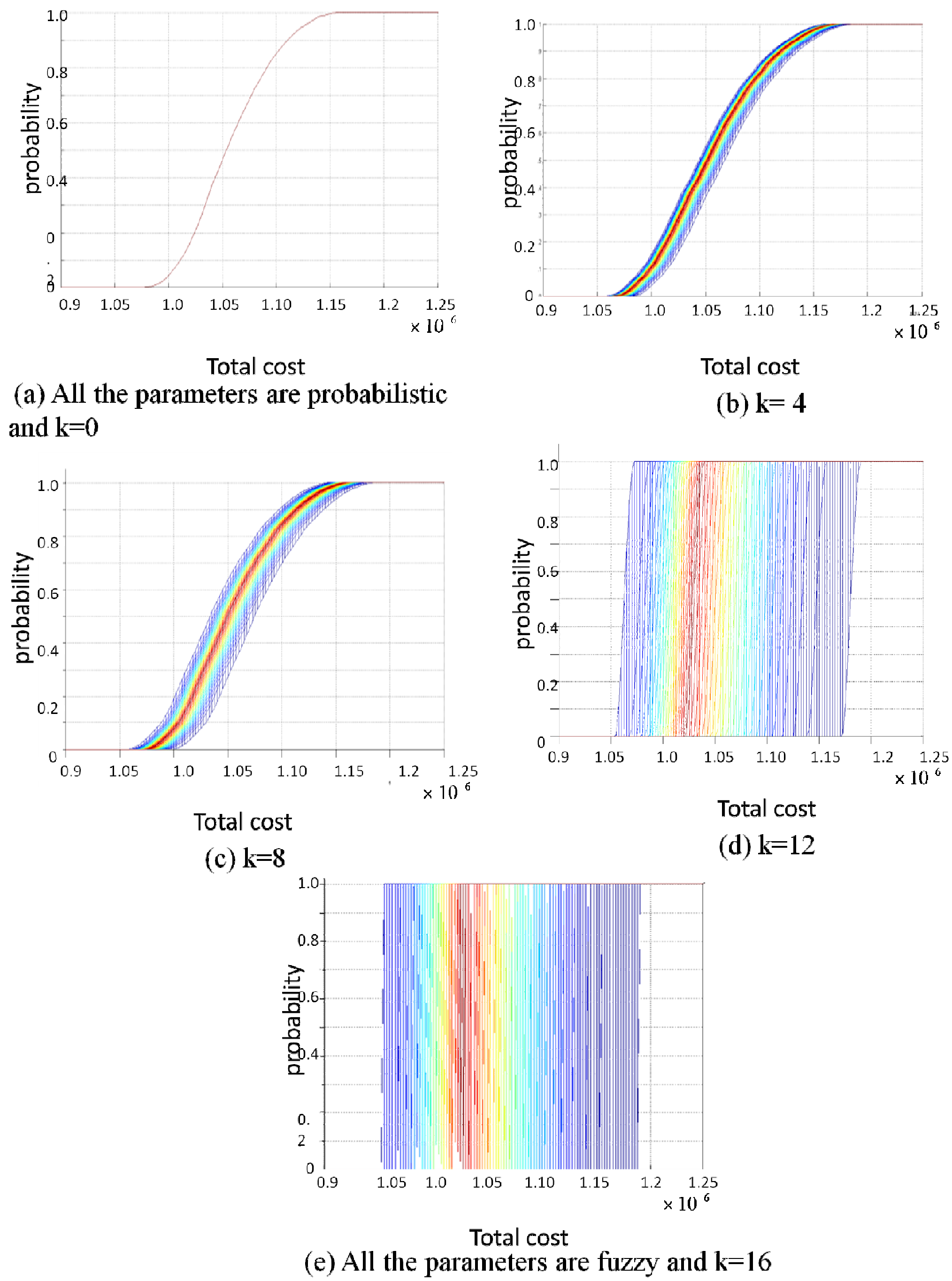
(d) k=12

(e) All the parameters are fuzzy and k=16

Figure 3.9 3D view of fuzzy CDF resulting from the output of FMCS for the highway overpass project; k indicates the number of fuzzy sets in each experiment

The x-y view of the fuzzy CDF is also represented in Figure 3.10. These figures illustrate the CDF bounds of the output of the experiments for different values of

k. As expected, for smaller values of k, the CDF function has less fuzziness, and the CDF bound is narrower.



(a) All the parameters are probabilistic and k=0

(b) k= 4

(c) k=8

(d) k=12

(e) All the parameters are fuzzy and k=16

Figure 3.10 x-y view of output results of Figure 3.9; k indicates the number of fuzzy sets in each experiment

The reasonable behaviour of the FMCS in the absence of fuzziness or randomness is also illustrated by these experiments. If a traditional Monte Carlo cost range estimating model is developed using the inputs of Table 3.2, the output will be exactly equal to the one shown in Figure 3.10(a). Therefore, in the absence of fuzziness, the results of the proposed methodology in Figure 3.10(a) will be exactly equal to the traditional CDF derived from the purely probabilistic Monte Carlo simulation method. Also, the results in Figure 3.10(e) indicate that when we have no randomness in the model, the CDF bound does not contain any probabilistic information. However, the fuzzy information can be viewed in the x-z view of the output in Figure 3.11. This example illustrates the reasonable behavior of the proposed methodology in the sense that the output is exactly equal to the output of the same model solved using the purely fuzzy cost range estimating method suggested by Shaheen et al. (2007).

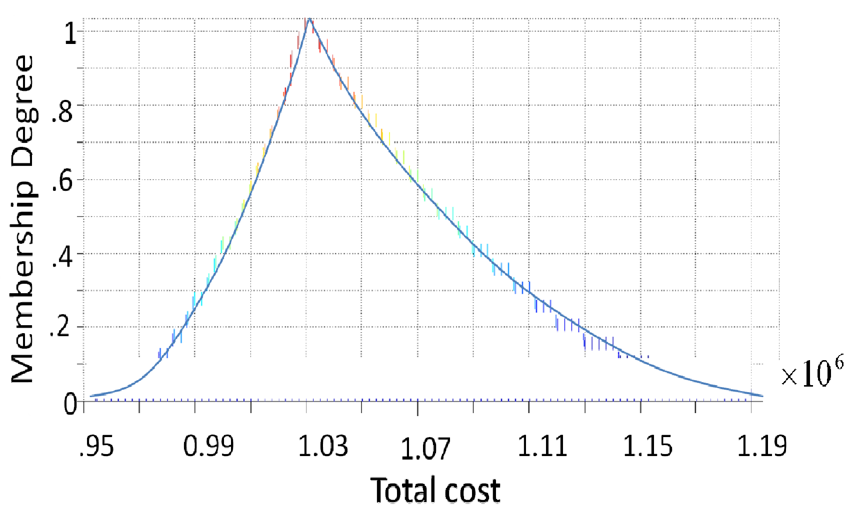
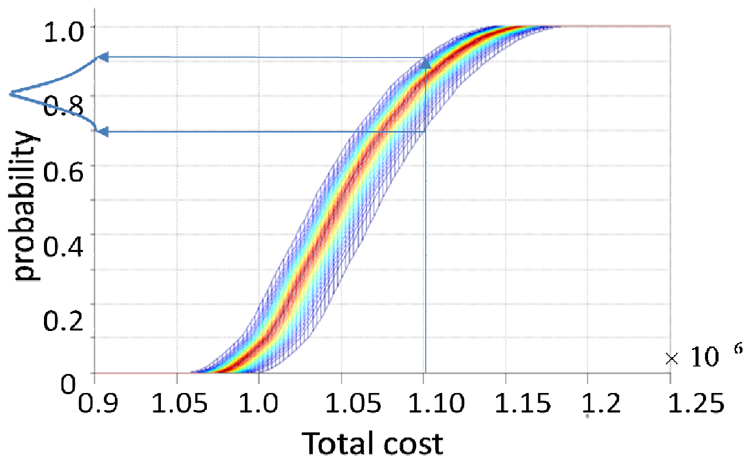


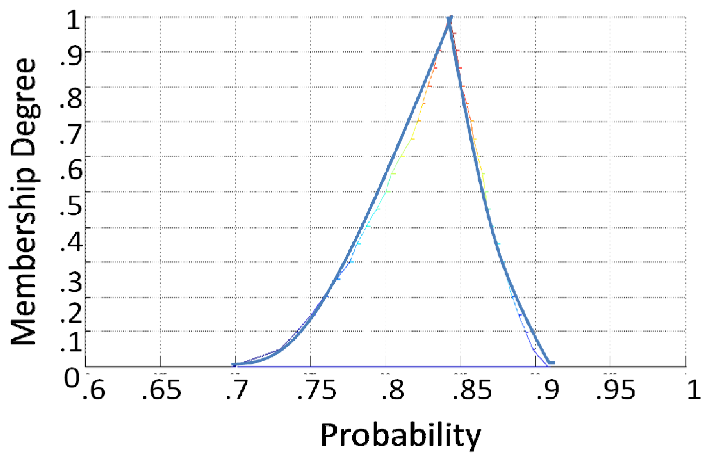
Figure 3.11 The fuzzy information of the output in the absence of randomness (k=16)

3.4.2 Decision Making Based on Fuzzy CDF

Similar to the CDF function resulting from Monte Carlo simulation, an estimator can use the fuzzy CDF of the total cost to estimate the probability of finishing the project within a certain budget. For example, using the CDF function for k equals 4 in which the first 4 uncertain variables of the example by Ahuja et al. (1994) are transformed to fuzzy sets, Figure 3.12(a) indicates how the probability that the total cost of the project will be less than \$1, 100,000 is calculated by assigning \$1, 100,000 to the x-axis of the fuzzy CDF. This probability is in the form of a fuzzy set, as shown in Figure 3.12(b). A fuzzy set can be defuzzified to get a crisp value and use that value for decision making. The centroid method is one of the most common methods for defuzzification, in which the defuzzified value is calculated by finding the center of the area under the membership function. By defuzzifying the fuzzy output of Figure 3.12(b) using the centroid method of defuzzification, we can state that the probability of finishing this project with \$1, 100,000 is about 0.82.



(a)



(b)

Figure 3.12 (a) Intersecting the fuzzy CDF to find the probability of not exceeding a specific threshold (b) The fuzzy set representing this probability

An arbitrary quantile can be used to find an appropriate contingency value for a project. Traditionally, this decision is made by considering a quantile value and using the CDF to find the output. In a fuzzy CDF, the arbitrary quantile is in the form of a fuzzy set. Figure 3.13(a) illustrates how the 80th quantile of the total cost of the project is calculated by intersecting the y-axis of the fuzzy CDF at y is equal to 0.80. The result indicates that, with 80% probability, a budget of around $1,095,000 is enough for recovering the total cost of the project (Figure 3.13(b)).

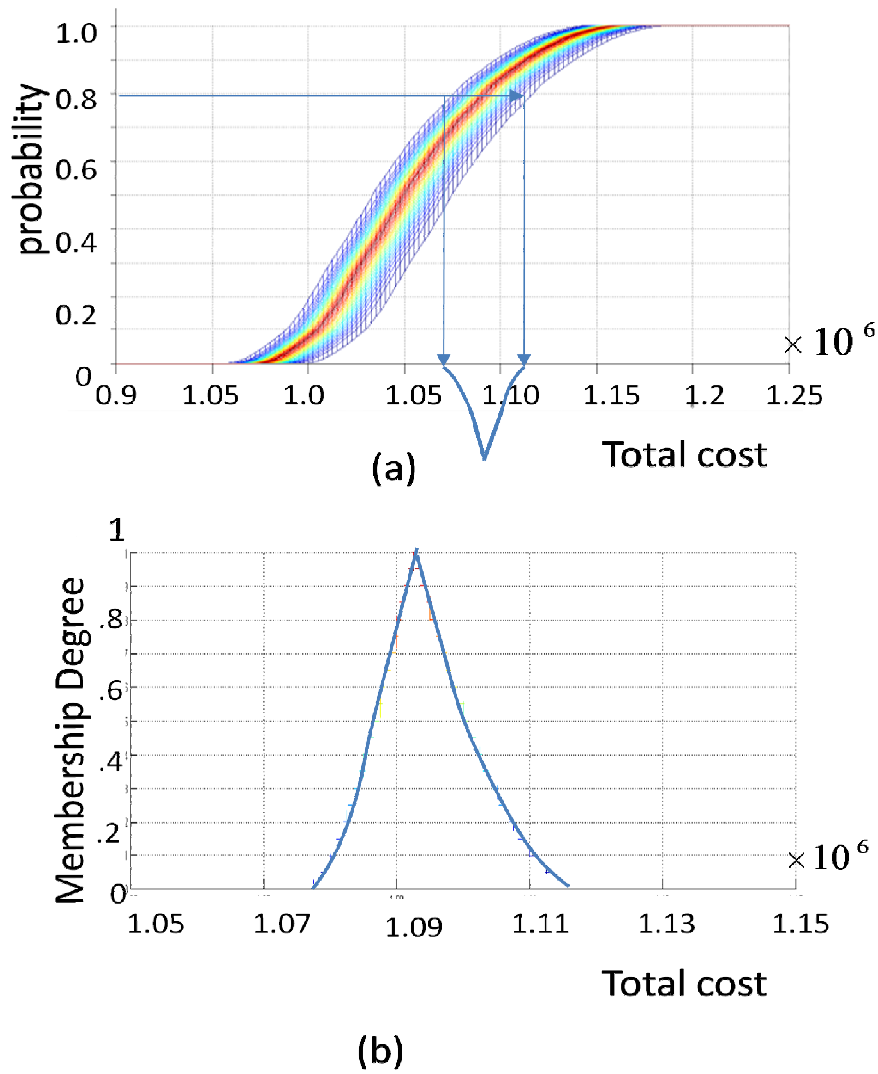


Figure 3.13 (a) Intersecting the fuzzy CDF to find an arbitrary quantile (b) The fuzzy set representing this arbitrary quantile

The real intent of FMCS framework is not to defuzzify the output results, but rather to indicate the fuzziness that exists in the output and to allow the estimator to use his/her subjective judgment in deciding on a final value. After obtaining the output fuzzy sets using the above-mentioned methods, the estimator has to decide on an alpha level to get a range of values. (Mauris et al. 2001). The final value should be selected from this range based on the optimistic or pessimistic view of the decision maker. For example, a manager may wish to estimate a final bid price based on the fuzzy set obtained from the 80th quantile of the project. If the decision maker chooses 0.4 for the alpha level the range of outputs will be [1,085,000 1, 100,000] (Figure 3.13(b)). Finally, the decision maker can choose the bid price from this range. For example, a conservative decision maker may go for the Sup value of this range, which is $1, 100,000.

3.5 Conclusions

This chapter proposes a Fuzzy Monte Carlo Simulation (FMCS) framework as a generalized form of Monte Carlo simulation for modeling construction projects. This framework is capable of considering both fuzzy and probabilistic uncertainty in a problem. In FMCS, the output is modeled using fuzzy random variables and fuzzy Cumulative Distribution Function (CDF) is introduced as a generalized form of CDF. Fuzzy CDF has the unique feature of representing both fuzzy and probabilistic uncertainty in a single figure. The proposed FMCS framework is capable of considering imprecise information in the form of fuzzy sets without assuming probabilistic information that is not actually available in a simulation model. Therefore, the decision maker is presented with the uncertainty in the output in the form of fuzziness and probabilistic uncertainty, and he/she can use subjective judgment and experience to make the final decision. Practical examples are suggested for applying the FMCS framework on real construction projects.

However, actual testing on real projects by industry personnel should be conducted to better justify the benefits that FMCS framework brings to the construction industry.

FMCS is used to develop a cost range estimating template for construction projects. The template is used for sensitivity analysis of the FMCS framework based on a highway overpass example. The results illustrate the reasonable behavior of the FMCS framework.

Finally, although the fuzzy CDF is developed as part of the proposed FMCS framework, the fuzzy CDF approach is a general method based on fuzzy random variables and may be used for risk analysis in any application, in which both fuzzy and probabilistic uncertainty are involved. For example, fuzzy CDF can be used in measurement theory to analyze the uncertainty of the data resulting from measurements in cases in which there is both probabilistic and fuzzy uncertainty (for example, Terán 2007).

CHAPTER 4 - COMBINED FUZZY AND PROBABILISTIC DISCRETE EVENT SIMULATION FOR INDUSTRIAL CONSTRUCTION

4.1 Introduction

The term "industrial construction" is used for construction of facilities for basic industries such as petrochemical plants, nuclear power plants and oil/gas production facilities (Barrie and Paulson 1992). Some parts of industrial construction projects can be processed in the controlled environment of the fabrication shop; however, there is no mass production in industrial fabrication shops, which distinguishes them from the category of job shops (Karumanasseri and AbouRizk 2002).

Construction projects are complex and associated with a high degree of uncertainty. As a result, it is difficult for planners to consider the combined impact of uncertainty of different products and resources and produce a reliable project estimate (Ahuja and Nandakumar 1984). Traditional management methods such as CPM/PERT fail to model the dynamic nature of these complex processes, because they lack certain modeling components such as probabilistic branching, resource interaction, and production cycling (Pritsker 1986). Moreover, most of the developed optimization algorithms (e.g., Hopp and Spearman 1997) are based on highly simplified assumptions (Song et al. 2006).

Discrete event simulation has been proposed as an indispensable problem-solving methodology for analyzing complex and uncertain processes such as construction projects (Halpin and Riggs 1992). Researchers widely apply simulation techniques to various industrial and construction processes (Banks 1998; Law and Kelton 2000).

The traditional approach for representing uncertainty in discrete event simulation models is probabilistic theory. Enough historical data are required to accurately estimate the probability of input parameters, yet subjectivity and lack of data regarding the parameters of an industrial construction project are very common, since there is no mass production and each product is unique. In these circumstances, fuzzy logic can be used for modeling the uncertainty of parameters based on experts' judgment. However the features of a product can be usually derived from a database, and the variation between the features of different products is considered random.

As discussed in Chapter 2, previous research has used fuzzy logic to model uncertainty in discrete event simulation models, yet it has not successfully combined both fuzzy and probabilistic uncertainty in the same model. In this chapter, a hybrid framework for discrete event simulation of industrial construction that can consider both random variations in the available data and fuzzy uncertainty resulting from expert's judgment is proposed. This framework provides a useful tool for more realistically modeling uncertainty in industrial construction for improved simulation. The proposed hybrid framework is discussed using a real case study of a pipe spool fabrication shop.

4.2 Pipe Spool Fabrication Shop

Pipe spool modules are used in developing modular construction units in refineries and oil-processing plants (Mohamed et al. 2007). The piping process involves drafting, material procurement and supply, shop fabrication including pipe spools and steel pieces, module assembly in the yard, and module installation on site. This process is very complicated and is associated with many uncertainties (Wang 2006).

The main activities for fabricating spools in a fabrication shop are cutting, fitting, and welding. Each spool is composed of a number of pipes that are welded together. A fitting component usually exists between two pipes. The joint between each fitting and a pipe is welded in the shop to produce the spool. For example, the spool in Figure 4.1 consists of 4 pipes and requires 7 welds.

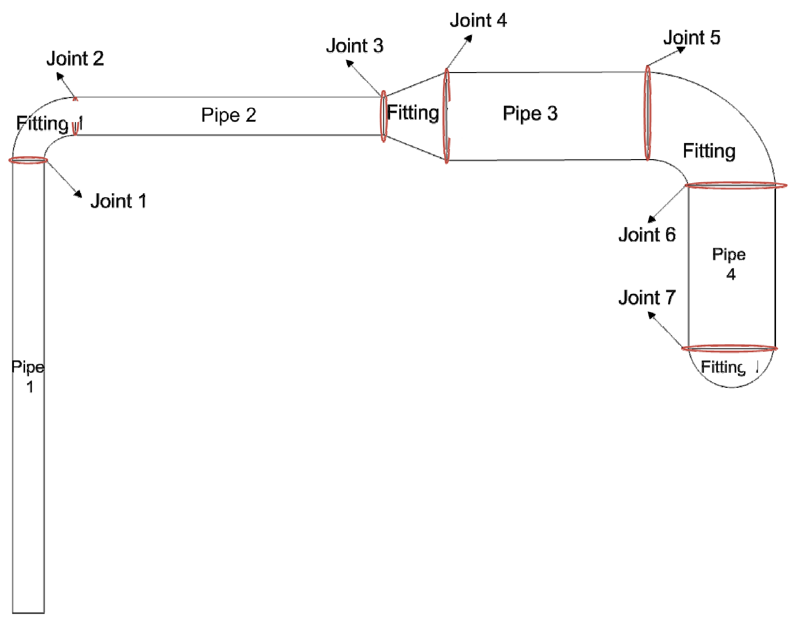


Figure 4.1 Pipes, fittings, and joints in a spool

For fabricating a spool in the shop, the pipes are first cut to their required size in a cutting station. Stations that are used for cutting in a fabrication shop could be different according to the type of material and diameters of the spools.

After cutting, the pipes are tagged together (fitted) and welded at each joint. The welding process includes roll welding and position welding. In roll welding, the pipe is welded by means of a roll welding machine (positioner machine) (Figure 4.2 (a)). Position welding is used when the pipe has long legs and cannot be roll welded (Figure 4.2(b)). Since the process of position welding is much slower compared to roll welding, fabricators try to find the sequence of steps that maximize roll welding and minimize position welding for each spool.

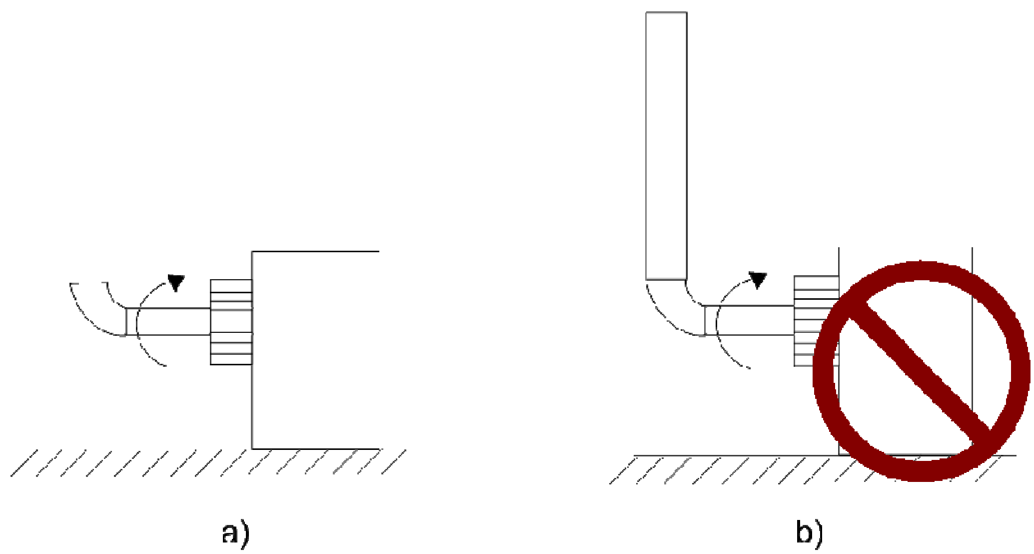


Figure 4.2 (a) Roll welding (b) Roll welding is impossible

Each spool is composed of a number of assemblies that can be fabricated only by a roll welding process. Different assemblies are then position welded to build the complete spool (Figure 4.3).

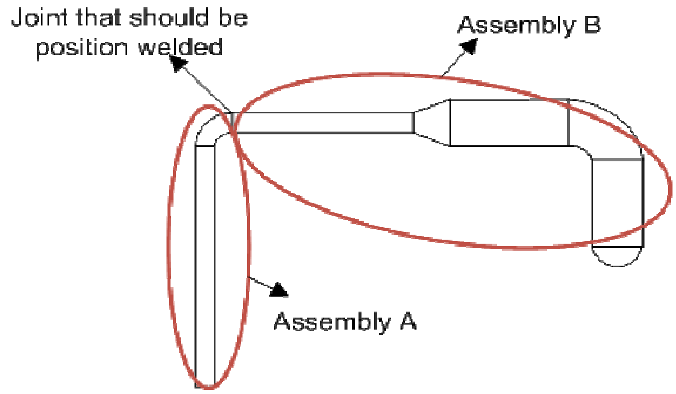


Figure 4.3 A spool is divided to some assembly parts that can be roll welded

Fitting and roll welding are done in two separate stations; there are usually two welding stations that are working with one fitting station. The fitters may fit one or more joints at a time before sending the spool for roll welding. The number of times that the product goes back and forth between fitting and welding stations depends on the number of joints and the structure of the spool (Figure 4.4). Also, different types of fitting and roll welding stations are used in the fabrication shop according to the characteristics of the spool. For example, for a long pipe we need a station that provides enough space for fitting and welding; and for a large diameter pipe, a welding station with a large roll welding machine is required.

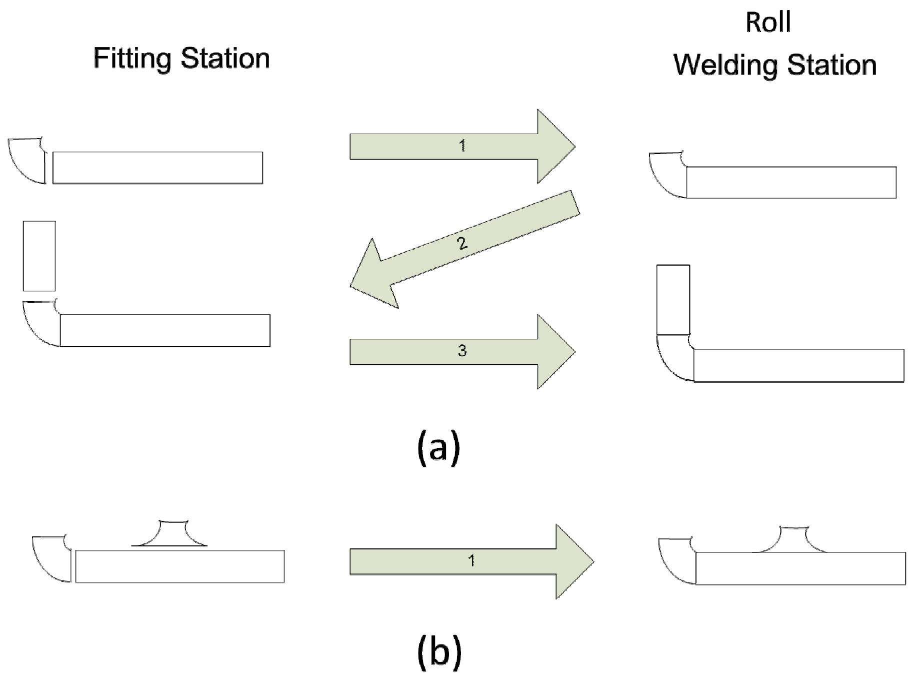


Figure 4.4 A product goes back and forth between fitting and roll welding station until it is completed

Fitting and position welding are done in the same place. There is usually one fitter and one welder working together in one station. A fitter brings all the finished components together and assembles them.

Quality control can be done at any stage of the process. Some of the spools may need hydro-testing, Post Weld Heat Treatment (PWHT), x-ray, or painting, depending on the required specifications from the owner.

4.3 Discrete Event Simulation of Pipe Spool Fabrication Shop

In this section, a discrete event simulation model for pipe spool fabrication shop is developed. For this purpose, a platform for modeling the raw materials in industrial fabrication is first developed. The platform is used to develop a simulation based decision support system using a real case study of a pipe spool fabrication shop.

In industrial fabrication, each product has its unique features and the duration and activity sequence can vary greatly from other products. In an industrial fabrication shop, such as pipe spool and steel fabrication, a product usually travels in the system in the form of raw materials or components of the product. During the fabrication process, different components are assembled together to fabricate the final product. To increase the accuracy of modeling fabrication processes and to better model the durations of the processes, a platform that can automatically model the raw materials and the assembly process of components of a product based on the unique features of a product is proposed. The process of pipe spool fabrication shop using this approach is modeled.

4.3.1 Modeling Approach

Products in industrial construction are usually decomposed into smaller assemblies to make the fabrication process easier; each assembly may have a number of detailed components. Therefore, each product does not travel in the system as one entity but usually travels as raw materials or different components. Since each entity is unique, the process of assembling and decomposing the elements depends on the entity's unique features. Traditional simulation models assign user-defined ID values to different entities of a product in order to simulate the assembly process (Wang 2006). In this section, the Work Breakdown Structure (WBS) of a Product Model (Song et al 2006) for modeling the assembly process is proposed. This approach can generate the raw material entities for a product, based on the product's unique features. It is also capable of automatically assembling the entities to generate a component or the final product.

This platform extends the function of the virtual shop modeling approach by Song et al. (2006) in order to model the flow of raw materials and components of a product as individual entities in a simulation model and to use the Product Model to estimate the duration of the activities.

Song et al. (2006) suggested a "virtual shop modeling system" to model the unique characteristics of each product entity in a simulation model. In their approach, a Product Model (PM) is defined for each entity that includes its physical features and its Work Breakdown Structure (WBS) features. An example of a PM of a spool is shown in Figure 4.5. Each part or component of a product can be represented by a node in the WBS.

During the fabrication of a product, some processes are performed on the raw materials, which are at the lowest level in the PM of an entity. Raw materials are then assembled together to produce higher level components, and this process continues until the final product is produced. For example, in the spool fabrication process, the cutting machine works on the pipe level (level 3 in Figure 4.5), roll welding is done on the assemblies (level 2 in Figure 4.5), the process of position welding takes place on the spool level (level 1 in Figure 4.5), and material handling can takes place at any level of the WBS of a spool. Different components of a spool can flow in a simulation model as different entities, so when a process requires a specific level in the WBS, the entity should be sent to the required level. Therefore, a level of the WBS can be assigned to each process.

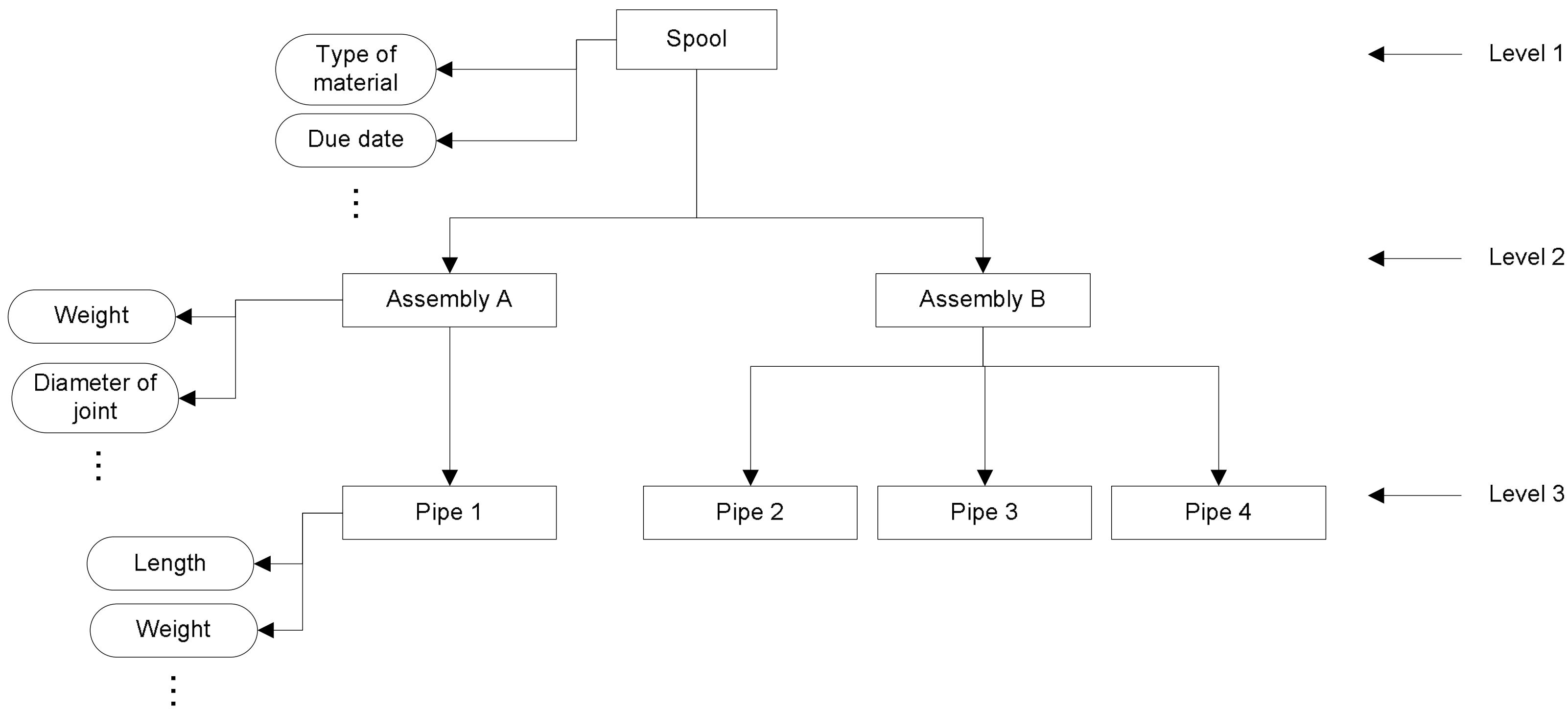


Figure 4.5 Product model including physical and WBS features

In the proposed methodology, raw materials or entity components of a product represent a node in the WBS. Since the entities that exist in a simulation model at the same time should be mutually exclusive, they cannot be ancestors or descendants of another entity in the WBS. For example, for a spool with a product model shown in Figure 4.5, we can have 4 entities representing “pipe 2”, “pipe 3”, “pipe 4”, and “assembly A” in a simulation model, but it is not possible to have “pipe 3” and “assembly B” at the same time in a model.

A level of WBS is assigned to each process in the simulation. Before an entity starts a process, the level of WBS is adjusted to the required level of that process. A “level adjusting” element is designed to assemble the entities based on their WBS automatically (Figure 4.6). For assembling an entity to an ancestor component, the level adjusting element checks the required components for the assembly process using the WBS of the entity. The entity waits until all the components arrive to the element, and the assembly process proceeds afterwards.

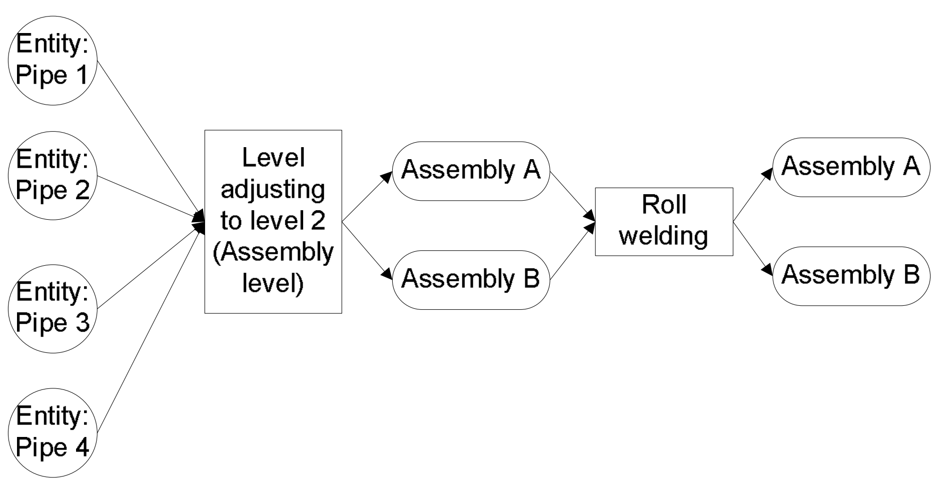


Figure 4.6 Level adjusting element for assembling an entity

To produce the raw materials at the start of the simulation, an element first generates each product and its PM and sends it to the level adjusting element to immediately decompose it to the lowest level of its WBS. Figure 4.7 shows how the level adjusting element decomposes an entity to its raw materials.

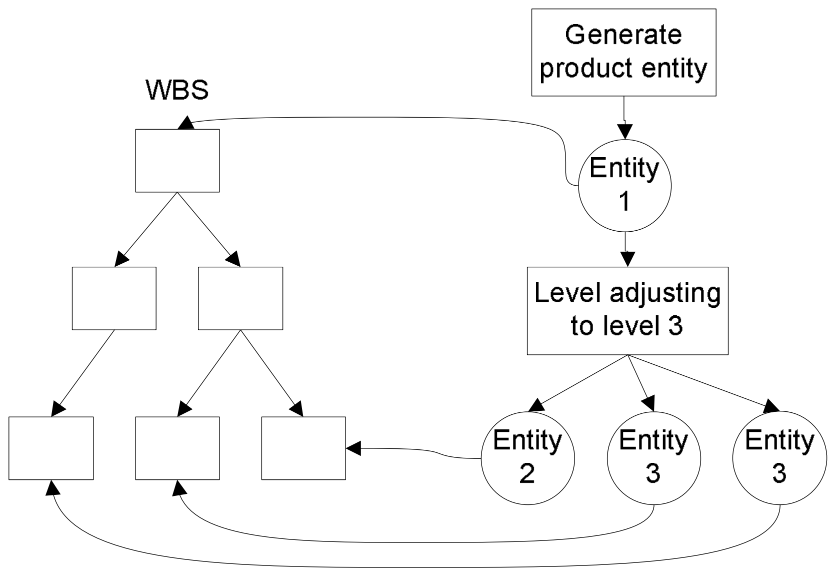


Figure 4.7 Decomposing an entity to its raw materials

Using this approach, we can have access to the unique characteristics of the materials in each activity based on its PM. Therefore, different methods can be used for modeling the effect of features of the products on the duration of activities depending on the data and information that is available for a process.

4.3.2 Discrete Event Simulation Model

The proposed methodology is used to develop a simulation based decision support model for an actual case study of a pipe spool fabrication shop. The model is capable of estimating the production and bottlenecks of the shop. It is also possible to use the model to explore different if-then scenarios to determine possible improvements in the shop. The developed model integrates a Visual Basic program with a discrete event simulation model developed in Simphony.NET©.

Simphony.NET© is an integrated simulation environment for building Special Purpose Simulation templates (SPS) (Hajjar and AbouRizk 2002). SPS templates allow an expert who is not necessarily knowledgeable in simulation to easily model a project using visual modeling tools. It provides a high degree of similarity to the actual construction process in a specific domain (AbouRizk and Hajjar 1998).

A SPS template in Simphony.NET© was developed to model the pipe spool fabrication process of an industrial construction fabrication shop in Alberta. Job characteristics are captured in the form of probabilistic distributions, and the "spool generator" element generates the spool's PM based on these characteristics. Simphony.NET© provides the capability of assigning different attributes to an entity. This feature has been used to assign a unique PM to each entity. The rest of the elements that have been developed for this model are as follows; these elements can be used for modeling any fabrication process and are not specific to pipe spool fabrication:

- Fabrication shop: The parent element of all elements in the fabrication shop.

- Station: Represents a station that is doing a specific fabrication process such as cutting, fitting, or welding. The type of component that the station requires is specified in this element.
- Level adjusting: Before processing an entity in a station, a "level adjusting" element adjusts the level of the entity to the required WBS level of its PM.
- Next station: This element determines the next appropriate station for an entity based on the entity's physical features, which are accessible from its PM, and the characteristics of the station.
- Material handling: This element models the process of handling materials within or in/out of the shop.
- Worker: This element represents different types of workers.
- Overhead crane: This element represents the overhead cranes in the shop that are used for handling heavy materials.
- Waiting file: The entities will wait in this element until they receive their required resources.

The above-mentioned elements have been used to model the pipe spool fabrication process of an actual fabrication shop. Different types of stations are considered for each process based on the size and specifications of the entities.

4.3.3 Estimating Input Values

The duration of processes can be modeled using probabilistic distributions to represent the variation of durations (Law and Kelton 2000). By considering the factors that affect the duration of an activity, the variance of the probability distribution function can be reduced. Therefore, by considering more factors we can decrease the uncertainty in the duration of different activities in a simulation model and increase its accuracy (AbouRizk and Sawhney 1993). Since the duration of processes such as cutting, fitting, and welding are highly affected by the spool features, the knowledge about the product model of each spool and its effect on the productivity is used to reduce the uncertainty and increase the reliability of the simulation model .In the proposed model, the durations of these processes are estimated by accounting for three factors: productivity values estimated by experts, amount of work units in each spool, and number of workers.

In the case study of the fabrication shop, historical data are provided in the form of productivity values which are the produced work units delivered by the man-hours used to produce them (Equation 4.1).

$$\text{productivity} = \frac{\text{Amount of work units}}{\text{Man}-\text{hours}} \tag{4.1}$$

Work unit amounts can be estimated at different levels of the WBS of a spool in the fabrication shop based on the number of welds, diameter of each weld, weld type, type of material and wall thickness. The company uses certain tables to account for the effect of these factors on the work unit amount. Because of the confidentiality issue, these excel sheets cannot be revealed. The productivities are recorded in the database for the main tasks such as cutting ($\text{Pr}_{\text{Cutting}}$), fitting ($\text{Pr}_{\text{Fitting}}$) and welding ($\text{Pr}_{\text{Welding}}$).

The productivity values of the historical data can be used for estimating the duration of a spool for a specific task. For example, assume that we would like to calculate the duration of welding for a spool ($\mathrm{Dur_{welding}}$). First, the work unit of that spool, ($\mathrm{WU_{spool}}$), should be calculated. Considering (w) workers are working on the spool, the duration can be calculated according to Equation 4.2.

$$\mathrm{Dur_{welding}} = \frac{\mathrm{WU_{spool}}}{\mathrm{Pr_{Welding}} * \mathrm{w}} \tag{4.2}$$

Many factors affect the durations of activities in the fabrication shop that are not considered in estimating the work unit amount. For example, roll welding and position welding are two different activities that are performed in two different stations. However, for calculating the work unit amount of weld, the effect of position welding or roll welding in the duration is not considered. As a result there is a variation in the productivity values in the shop that can be reduced by explicitly considering these factors. However, available productivity values in the historical data cannot show the real variance in the productivity for processing different spools, since the historical productivities are recorded based on the work units that are produced by the whole shop in a given period of time.

To refine the durations based on other factors, the average value of the historical data is combined with expert judgment, by asking the expert to compare the duration of performing a task under a specified situation with the average duration. For example the expert may say "the duration of performing position welding is about twice of the average productivity for welding". The duration for position welding ($\mathrm{Dur_{PW}}$) can be estimated based on this statement using Equation 4.3

$$\mathrm{Dur_{PW}} = 2 * \mathrm{Dur_{welding}} \rightarrow \mathrm{Dur_{PW}} = 2 * \frac{\mathrm{WU_{spool}}}{\mathrm{Ave(Pr_{Welding})} * \mathrm{w}} \tag{4.3}$$

To get a range for the duration of position welding that can represent the variance in this process; the expert is asked to determine the maximum and minimum values of the ratio between the duration of position welding and the average duration of welding. The expert may say it could range from 1.5 to 2.5 of the average duration. Therefore, a triangular Probability Density Function (PDF) function, f(x), can be developed using these three values, where x is the ratio between the duration of position welding to the average duration of welding (Figure 4.8).

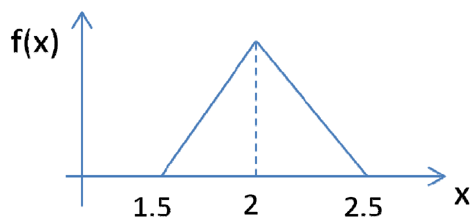


Figure 4.8 A triangular PDF, f(x), is defined for the ration(x) between the duration of position welding to the average duration of welding

Developed PDF, f(x) is used to estimate the duration of position welding by sampling the ratio form the PDF and using Equation 4.4.

$$\mathrm{Dur}_{\mathrm{PW}} = \mathrm{ratio} * \mathrm{Dur}_{\mathrm{welding}} \rightarrow \mathrm{Dur}_{\mathrm{PW}} = \mathrm{ratio} * \frac{\mathrm{WU}_{\mathrm{spool}}}{\mathrm{Ave}(\mathrm{Pr}_{\mathrm{Welding}}) * \mathrm{w}} \quad (4.4)$$

The same approach is used for estimating the duration of other activities such as roll welding for small spools, roll welding for large spools and small cutting stations, etc.

A Visual Basic (VB) application has been developed to control the input to the simulation model, making its use more readily accepted by industry practitioners (Figure 4.9). Since the layout is not fixed in the fabrication shop, the user can change the shop layout as well as the job characteristics and resource specifications through the user interface. This feature also provides the capability of experimenting with different if-then scenario to come up with the best possible shop layout. The user can also update resource specifications such as, number of stations, productivity of each station, the number of workers that are required in each station and the total number of workers. The VB program analyzes the simulation results and highlights the bottlenecks and underused resources through the interface (Figure 4.9).

The simulation model is validated by comparing the estimated produced work units by the simulation model with the actual produced work units of the shop in a specific period of time. A number of experiments are performed for different periods in the fabrication shop. For each experiment, the job characteristics, number of workers and shop layout are specified by the managers. The model runs for various times to use different samples of the PDFs defined for the durations of the activities.

The results of the model are very satisfactory to the managers of fabrication shop; the average produced work units estimated by the model was very close to the actual produced work units experienced by the fabrication shop, with less than 5% error for all of the considered periods. Error percentage is calculated according to Equation 4.5. (ABS is the absolute value in this equation).

$$error\% = ABS\left(1 - \frac{Average\ work\ units\ estimated\ by\ the\ model}{actual\ work\ units\ produced\ by\ the\ fabrication\ shop}\right) * 100 \quad (4.5)$$

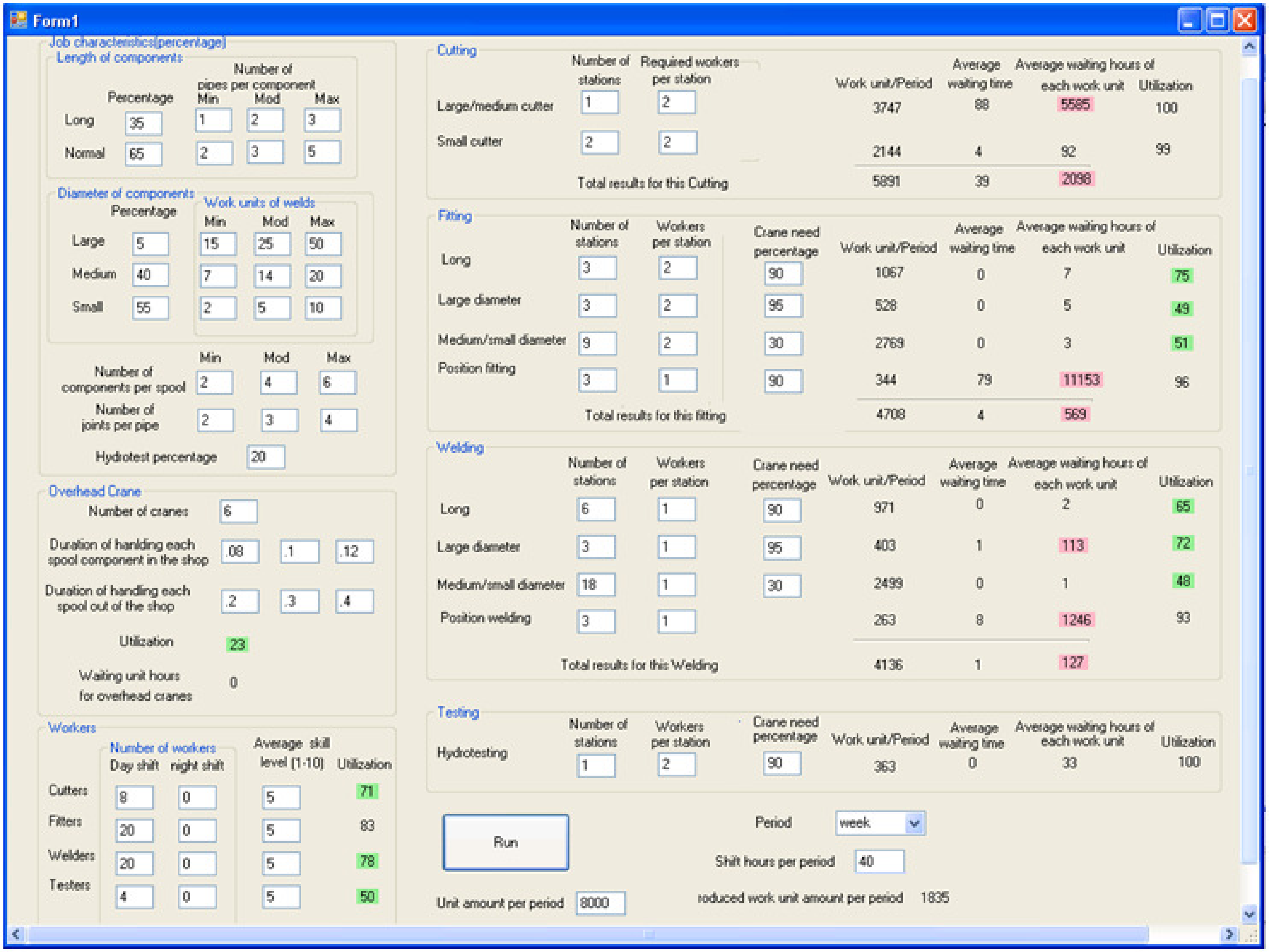


Figure 4.9 User interface for simulation model developed in Visual Basic

4.4 Improving Uncertainty Assessment in Discrete Event Simulation Using a Combined Fuzzy and Probabilistic Approach

In the developed simulation model for pipe spool fabrication shop in Section 4.3, the PM of the spools are derived based on sampling from PDFs of the job characteristics provided by experts. This method is appropriate in situations that we do not have the exact information of the spools, for example, before the contract, when we are at the bidding stage. However, the company usually has access to the specifications of the spools after the contract. If a database contains all the specifications of the available spools, the accuracy of the simulation model can be improved by connecting the model to the database and developing the PM of the spool based on the actual information that is provided in the database. In this way, the uncertainty in the model will decrease, each spool can be tracked in the fabrication shop, and the model can be further used for scheduling purposes.

While connecting the model to the database will decrease the uncertainty in the PMs of the spools, fuzzy logic can be used to better represent the uncertainty in the durations of the activities resulting from experts' judgment. In the approach proposed in Section 4.2, experts' judgment and the PM are used to estimate the PDF of the duration of activities by providing the minimum, maximum and most likely value. Other researchers also try to convert experts' knowledge into probabilistic distributions (see Ahuja et al. 1994; Garthwaite et al. 2005). However, there are some criticisms on performing probabilistic analysis on subjective and linguistically expressed data, as the subjective reasoning of individuals may not be appropriate for objective scientific conclusions (Goldstein

2006). In other words, the information gained from experts is subjective and contains ambiguity, and there is a chance of introducing artificial knowledge that is not actually available to the model when using probability values gained from experts (Guyonnet et al. 2003).

Fuzzy logic is an appropriate alternative for expressing the information gained from experts. Various methods exist for developing fuzzy sets based on expert judgment, as discussed in Chapter 2. For example, in the method that is developed for estimating the duration of position welding in Section 4.3.3, we can model the ratio between the duration of position welding and average duration for welding using a fuzzy membership function, μ(x), instead of the PDF, f(x). Therefore, a fuzzy set *A* can represent the ratio x between the duration of position welding and duration of welding. The required amount of working units for position welding ($\mathrm{WU}_{\mathrm{postion}}$) can be derived from PM of the spool, as discussed in Section 4.3. Therefore, the duration for position welding, ($\mathrm{Dur}_{\mathrm{PW}}$), for a spool with (w) number of workers, can be calculated from Equation 4.6.

$$\mathrm{Dur}_{\mathrm{PW}} = \mathrm{A(x)} * \mathrm{Dur}_{\mathrm{welding}} \rightarrow \mathrm{Dur}_{\mathrm{PW}} = \mathrm{A(x)} * \frac{\mathrm{WU}_{\mathrm{postion}}}{\mathrm{Ave(Pr}_{\mathrm{Welding}}) * \mathrm{w}} \tag{4.6}$$

Since the values of the working unit amount and average productivity of welding are real numbers, fuzzy arithmetic can be used to find the duration of position welding as a fuzzy set. This approach for calculating the duration of the activity is illustrated in Figure 4.10.

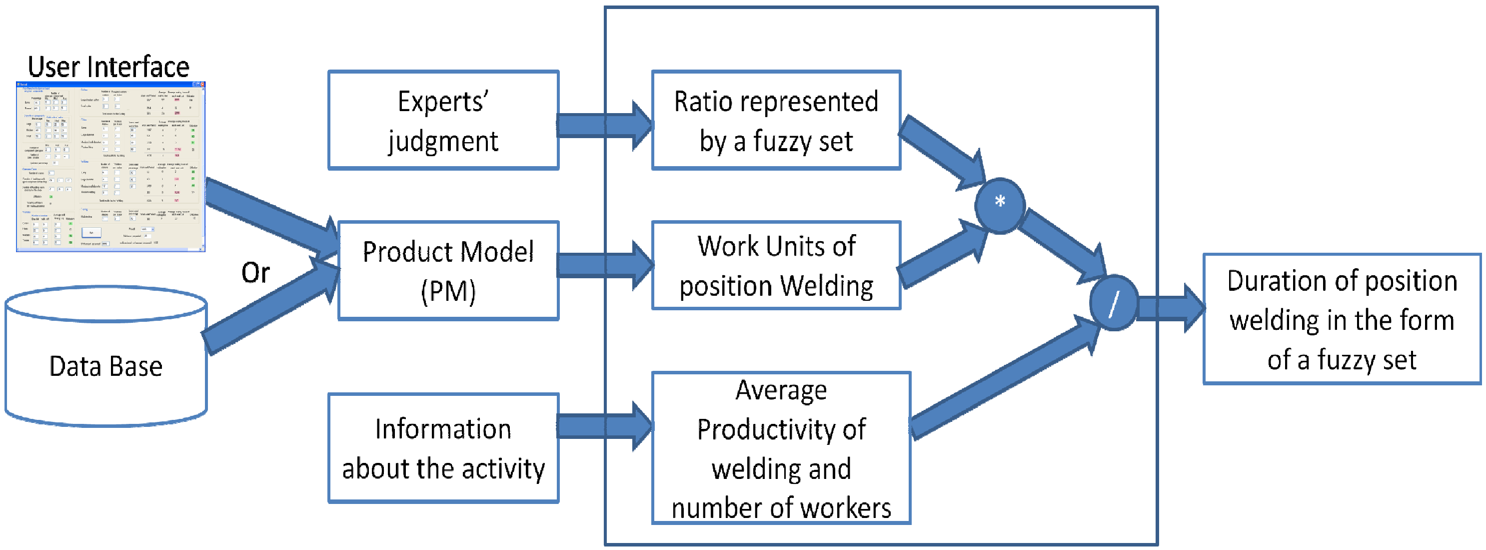


Figure 4.10 Calculating the duration of position welding in the form of a fuzzy set based on the PM and expert's judgment

Different methods can be used to consider the effect of different factors on the duration of construction activities based on fuzzy logic (for example, Ayyub and Haldar 1984). The method suggested in this section is just an example appropriate for the case study of pipe spool fabrication shop. In a general, for an industrial fabrication process, the duration of the activity should be estimated based on different factors such as product features, characteristics of the resources, and environmental factors. Expert judgment is used to express the effect of different factors on project duration. Finally, the uncertainty regarding the duration can be modeled using fuzzy sets to represent the vagueness and uncertainty resulting from expert judgment (Figure 4.11).

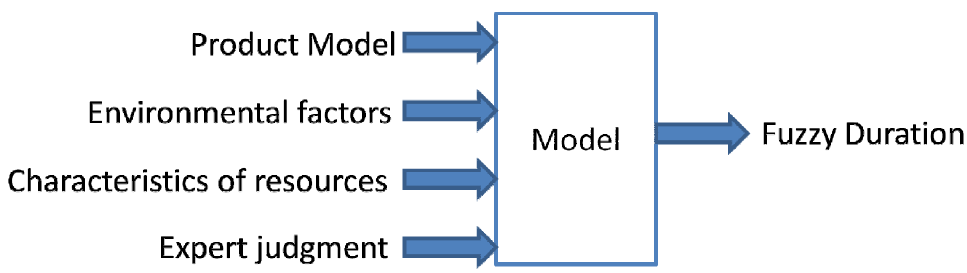


Figure 4.11 Estimating activity duration in the form of a fuzzy set

Using the proposed approach, we need to solve a simulation model in which the duration of each activity for the spools is a fuzzy set. Usually the fuzzy durations are defuzzified (Shaheen 2005) or converted to a PDF (Ayyub and Haldar 1984) to be used in discrete event simulation. However, as discussed in Chapter 2, there is no fully accepted way of transforming one type of uncertainty to another, and the defuzzified value cannot represent the uncertainty exists in the inputs.

Fuzzy discrete event simulation can be applied to use the fuzzy durations directly in the simulation model. The simulation time in the fuzzy discrete event simulation is in the form of a fuzzy set, as described in Chapter 2. Therefore, any statistics that are calculated based on the simulation time are in the form a fuzzy set. For example, cycle time of a spool is calculated based on the arrival time of the spool (t_{start}) and the time when the spool leaves the shop (t_{end}) using Equaiton 4.7. Since the times t_{start} and t_{end} are fuzzy sets, the estimated cycle time will be in the form of a fuzzy set, as well.

$$Cycle\ Time = t_{end} - t_{start} \tag{4.7}$$

Therefore, using fuzzy discrete event simulation, each observation of the outputs that is calculated based on simulation time, such as cycle time of the spool, is in the form a fuzzy set. However, the managers are not only interested in the outputs regarding each observation of the products, but they are also interested in the overall view of the project. For example, they would like to analyze the cycle times of different spools. In this case, we have a number of observations of different fuzzy sets and fuzzy random variables can be used to model this output. Also, fuzzy CDF can be developed for making decisions based on the output results, as discussed in Chapter 3.

In a general fabrication process, the proposed framework can be summarized in the following steps:

1. Model the activities and resources of the industrial fabrication process.
2. Generate the entities for the products and their product model using a database.

3. For each activity, compose and decompose entities to the required level of the PM.
4. Estimate the duration of each activity in the form of fuzzy set based on the PM, experts' judgment, resource characteristics, and environmental factors.
5. Use fuzzy discrete event simulation to run the model.
6. Collect the model outputs that are in the form of fuzzy sets.
7. Use fuzzy random variables and fuzzy CDF to analyze the collected outputs of the simulation models to present the overall view of project.

The approach that is suggested in this thesis enables the use of obtained fuzzy durations directly in the simulation model and performing fuzzy discrete event simulation. The output is in the form of a number of fuzzy sets that have random variations. The fuzziness in the output represents the uncertainty resulting from experts' judgment. The variation between fuzzy sets is the result of the possible variations in the characteristics of recourses and the environmental factors, as well as the difference between the product models of different spools. Therefore, the output can be modeled using a fuzzy random variable. To implement the proposed framework, possible methods for developing fuzzy durations based on expert judgment for an industrial fabrication process should be investigated. Also, various approaches for developing fuzzy discrete event simulation for industrial fabrication processes should be analyzed, and an appropriate method should be implemented.

4.5 Conclusions

We have developed a platform for simulating industrial fabrication processes that is capable of simulating a process to the level of raw materials and components of a product to estimate the duration of different activities and model the sequence of activities. The use of WBS of a Product Model to model the assembly process is proposed. This methodology allows the assignment of different levels of WBS to different processes. A node in the WBS is assigned to each entity, and a level adjusting element is designed that can automatically assemble or decompose the entities to the required level of each process. Expert judgment has been used to estimate the Probability Density Function (PDF) for the duration based on the PM of a product. This approach has been implemented using an actual case study to develop a simulation based decision support system for a pipe spool fabrication shop. The results show that the method is practical and useful. An SPS template that can be used for any industrial fabrication process has been developed in Simphony©.

To improve the modeling of the uncertainty in the input parameters, fuzzy sets are proposed instead of PDF for modeling the duration of the activities that are derived based on experts' judgment. Finally, a combined fuzzy and probabilistic discrete event simulation framework is proposed to consider the fuzzy durations of the activities, as well as the variation in the characteristics of resources, environmental factors, and product models of the entities. Future research should be conducted to implement the proposed framework and compare the results with a model using only the probabilistic type of uncertainty.

CHAPTER 5- CONCLUSIONS AND RECOMMENDATIONS

5.1 Research Summary

Simulation modeling is a powerful tool for capturing uncertainty in construction projects. The traditional approach for representing uncertainty in construction projects is probabilistic theory. Comprehensive historical data are required to accurately estimate the probability of input parameters, yet subjectivity and lack of data regarding the parameters of a construction project are very common. In these circumstances, fuzzy logic can be used for modeling the uncertainty of parameters based on expert judgment. Since subjectivity and a lack of data usually exist in some of the parameters affecting a construction project, a reliable framework is required to address both types of uncertainty in the form of randomness and fuzziness in the inputs of a simulation model. Different simulation methods may be applied to a model depending on the structure of the problem. In this research, we focused on two types of simulations: (1) Mont Carlo Simulation, and (2) Discrete Event Simulation. Monte Carlo simulation is applied to a model that does not depend on time, while discrete event simulation is time-based and can be used to analyze the sensitivity of dynamic schedule and resource constraints to unexpected construction scenarios.

The literature suggests two main approaches for solving a Monte Carlo simulation that has both fuzzy and probabilistic inputs: (1) transforming one type of uncertainty to another before processing the model, and (2) keeping the uncertainties in their original forms while processing the model. There is no single accepted method of transforming fuzzy sets to PDF or vice versa. Furthermore, even in the second approach, the output is analyzed by considering only one type of uncertainty or by representing fuzziness and randomness in other forms based on the theory of evidence. A Fuzzy Monte Carlo Simulation (FMCS) framework that can accept both fuzzy and probabilistic inputs for risk analysis of construction projects is presented in Chapter 3. In FMCS, the output is modeled using fuzzy random variables, and the fuzzy Cumulative Distribution Function (CDF) is introduced as a generalized form of CDF. Fuzzy CDF has the unique feature of representing both fuzzy and probabilistic uncertainty in a single figure. In fuzzy CDF, random and fuzzy uncertainties are represented explicitly to allow the decision maker to completely understand the origins of each type of uncertainty. FMCS is used to develop a cost range estimating template for construction projects. The template is used to perform a sensitivity analysis of the FMCS framework based on the example project of a highway overpass. The results illustrate the reasonable behaviour of the FMCS framework.

A hybrid framework for discrete event simulation of industrial fabrication that considers both fuzzy and probabilistic uncertainty is proposed. Although previous research has used fuzzy logic to model uncertainty in discrete event simulation models, it has not successfully combined both fuzzy and probabilistic uncertainty in the same model. In reality, we usually face both types of uncertainty simultaneously in construction simulation. To develop a combined fuzzy and probabilistic discrete event simulation model for industrial fabrication, first of all, a platform for simulating industrial fabrication processes is developed that is capable of modeling the products to the level of raw materials. A node in the WBS is assigned to each entity, and a level adjusting element is designed that can automatically assemble or decompose the entities to the required level of each process. Expert judgment has been used to estimate the Probability Density Function (PDF) for the duration based on the Product Model (PM) of a product. This approach has been implemented using an actual case study to develop a simulation-based decision support system for a pipe spool fabrication shop. The results show that the method is practical and useful. An improvement on this approach is suggested by using fuzzy sets instead of PDF for modeling the duration of the activities that are derived based on expert judgment. Finally, a combined fuzzy and probabilistic discrete event simulation framework is proposed to consider the fuzzy durations of the activities as well as the random variation in the characteristics of different products in the shop.

5.2 Contributions

This research provides a generalized framework for Monte Carlo simulation that is capable of considering both fuzzy and probabilistic inputs. It also suggests a framework for discrete event simulation to explicitly consider both fuzzy and random types of uncertainty. Therefore, the modeler can benefit from the rich information provided by data as well as by capturing the ambiguity in expert judgments. The following major contributions are made in this thesis:

1) A Fuzzy Monte Carlo Simulation (FMCS) framework is developed as a generalized form of Monte Carlo simulation. This framework allows both types of uncertainty to be captured separately in Monte Carlo simulation for more realistic results.
2) The fuzzy Cumulative Distribution Function is proposed for the first time in this research as a generalized form of CDF. Although fuzzy CDF is developed as part of the FMCS framework, it is a general method based on fuzzy random variables and may be used for risk analysis in any application in which both fuzzy and probabilistic uncertainty are involved.
3) A new framework for simulation of industrial fabrication capable of modeling the products to the level of their raw materials is proposed. As a result, the effect of the characteristics of each component of a product on the duration of different activities is considered for use in discrete event simulation.
4) A methodology based on fuzzy logic is proposed for incorporating expert judgment to estimate the duration of activities for different product characteristics.
5) A consideration of both fuzzy and random uncertainty in a discrete event simulation model is suggested. A framework for simulation of industrial fabrication processes is proposed in which the duration of the activities are presented using fuzzy sets that are derived according to the Product Model of each entity.

5.3 Recommendations for Future Research

In the course of this thesis, numerous areas that have the potential for future research have been identified. The areas that can be investigated in greater detail are as follows:

1) Actual testing of fuzzy cost range estimating template in the industry should be conducted to better justify the benefits that this template brings to the cost range estimating of construction projects.
2) The Fuzzy Monte Carlo Simulation framework is implemented for cost range estimating. Implementing this framework in other areas such as construction project scheduling can indicate the practical aspects and the wide impact that FMCS framework can have on construction management.
3) Although the behavior of FMCS is verified by comparing the results with traditional Monte Carlo simulation, further research is required to find appropriate validation methods in order to evaluate the performance of the proposed methodology. For this purpose, validation criteria should be defined as part of formulating the research problem.
4) Currently, minimum t-norm is used to perform fuzzy arithmetic as part of the FMCS framework. The effect of other t-norms in FMCS framework shall be experimented. The best t-norm may be found in different applications to better satisfy the user.
5) Fuzzy CDF is proposed as a general approach based on fuzzy random variables. However, only Infinum and Supernum values of the alpha-cuts

are used for the development of the fuzzy CDF that can be improved in future research.

6) The methodology that is developed for estimating the duration of activities based on product characteristics can be improved by using other approaches such as fuzzy expert systems.
7) More case studies should be conducted to show the capability of the combined fuzzy and probabilistic discrete event simulation framework for modeling industrial fabrication processes using Product Model (PM).
8) The simulation model that is developed for pipe spool fabrication can be connected to the database of the company to read the exact information of the pipes from the data base and create more accurate Product Models (PM) for the entities in the simulation model.
9) The method proposed for combined fuzzy and probabilistic discrete event simulation should be investigated in more detail and implemented for pipe spool fabrication or other case studies. The first step for implementation of this framework is to develop a fuzzy discrete event simulation model. For this purpose, a fuzzy ranking method should be selected and implemented within a discrete event simulation model.

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